LEVERAGING CONFIRMATORY PROGRAM EVALUATION TO STATISTICALLY ASSESS THE EFFECTIVENESS OF THE UPWARD BOUND MATH AND SCIENCE PROGRAM AT TEMPLE UNIVERSITY, 2008–2021

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ABSTRACT

The Upward Bound Math and Science (UBMS) program at Temple University (TU) seeks to guide first-generation, low-income high school students from Philadelphia in their quest to obtain postsecondary STEM degrees that lead to related careers. This study aims to evaluate the efficacy of the program by analyzing its students' performance in light of its own goals and also in view of those of its sister program, The Upward Bound (UB) program. Primarily, this study uses Confirmatory Program Evaluation to ascertain which programmatic elements predict outcomes associated with indicators of STEM interest. Program leaders in TU's College of Education and Human Development provided data for the study. Data came from 2015–2021 annual performance reports, containing information on 374 former UBMS student participants as well as 483 former UB students. Findings indicate that UBMS students pursued postsecondary enrollment at a significantly higher rate than UB students. Results also suggest that UBMS students' grade level upon program entry was a significant direct negative predictor for how long they were affiliated with the program. In addition, students' grade level upon program entry was a direct positive predictor for whether they obtained a rigorous course of study. Community service involvement was a significant negative predictor for whether students completed advanced math courses. None of the predictors yielded a significant effect in either of the two outcomes by way of a third, mediating variable. Implications of the study suggest that alliances between principal investigators, program administrators, and statisticians—ultimately through mixed-methods approaches—may offer valuable insight regarding the evaluation of UBMS and programs like it.

This dissertation is dedicated to Genevee V. Dillard, my mother,

whose doggedness and resilience set the template for me to

learn the art of making lemonade from lemons

and harnessing momentum from

virulent storms.

ACKNOWLEDGMENTS

A famed inspirational speaker and author declared that "two main categories of people are needed in your circle—those who give you the necessary support to accomplish your dreams and those who become beneficiaries of what you achieve." Such words suggest a reality of interdependence between the human species, one that shuns any sense of being dubbed a self-made champion or a lone-rising star. In this spirit, I pay homage to my own village and those who have supported me in all of my victories, especially this one.

As a son of the South, I learned early on the value of working hard and being appreciative. Through the encouragement of a loving grandmother, who mostly took on the task of rearing me when she should have been enjoying a life of retirement, I offer a nod of thanks. The spiritual seeds she sowed in me have kept me grounded amid all my successes and struggles. Her spend-a-little, save-a-little advice has always helped me value a dollar and only pursue investments—like this adventure—that will aid me in the long run. Her driving me to high school daily showed me the love actions behind her mere words. I thus acknowledge the late Geneva E. Dillard.

In addition to developing a solid work ethic, I learned the art of persistence and perseverance. Witnessing my mother weather life's storms as a survivor of abuse helped me understand resilience and determination, key qualities necessary when pursuing studies in higher education in general and in a doctoral program specifically. Seeing her continue on with life, always wearing a smile and treating people right has always remained etched in my mind as an example for dealing with adversity. Moments that

presented challenges during this dissertation process seemed to be less daunting when I kept it all in perspective in the grand scheme of life, remembering how she overcame. It was her steadfastness and endurance that won. For these, I acknowledge Genevee V. Dillard.

This doctoral journey has been replete with excitement, angst, and pain. I cannot fathom how I would have made it through without the knowledge, expertise, and humility of Dr. W. Joel Schneider, my advisor. Doc! What am I going to do with my Friday afternoons now? I have gotten so used to our rhythm of sharing, growing, and facing my bouts with R. You helped me understand that the journey is just as important as the destination. You have been a great professor and mentor. From your stepping in to offer me assistance with “challenging” faculty members to cheering me on virtually during my New York City marathon run, you have been an advisor’s advisor—soft-spoken yet firm. I will pay it forward and use yours as a template if I ever have to serve in that capacity.

To my Dissertation Committee, you have been a tremendous support system for me during this adventure. Thank you, Dr. Sarah Cordes, for giving me my first dose of research reality in the Research Design and Methods course. I appreciate your listening ear as I initially stumbled to find my way to a research topic and for leading me to Dr. Johnson. To Dr. Jennifer Johnson, I appreciate your willingness to entertain an email “out of the blue” from a total stranger and suggest the program on which I would eventually base my dissertation. Thank you also for keeping me abreast of those pesky graduate school deadlines and forms. Thank you, Dr. Juliet Curci for your enthusiasm in sharing the data for this project as well as for chats and detailed emails about the program’s history. I am grateful that you trusted my advisor and me with the data and hope that I did

justice with the analysis. I am also grateful to Director Jody Markley for your patience with me and insight on the Upward Bound Math and Science Program. Though not on my committee, you took of your precious time to school me on many of the program's nuances that I would not have been privy to otherwise. To Dr. Christopher McGinley, I appreciate your sage advice in helping me navigate pivotal crossroads in the program. Further, I appreciate you, Dr. Armando X. Estrada, for formally teaching me the rudiments of program evaluation and helping to shape my dissertation in its initial phase.

It seems disingenuous not to tell the complete truth. This is my second time attempting to earn a doctorate. While I forego details here about the first rough experience, I have learned that things in life happen for a reason. After leaving the former university disappointed and feeling rejected, I took it as an opportunity to rebound and grow. Two decades later, I decided to give it another go, from ground zero. The nets that snagged me the first time have been transformed into webs of unwavering support this second time around. A little wiser and more hip to the politics of the journey, I made it to the finish line on this occasion.

I have learned much from my fellow cohort members. I remain fond of Randy and Erika, my first group project "partners in crime" in the program. And I consider Andrew a close friend. I continue to be propped up by countless friends, family, and the prayers of my church tribe, both near and far. I am thrust forward because all of you have recognized, nurtured, and watered the seeds of excellence in me that keep on sprouting. I am well aware that I am not an island unto myself. I am the sum of all the parts that have influenced me—the goods, the bads, the uglies. I will indeed strive to represent those well who have egged me on and made it possible for me to fly.

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CHAPTER 1

INTRODUCTION

Researchers have dedicated much of their resources and time investigating educational intervention programs and their effects on students. Arguably, such programs serve as intermediaries whose mission is to interrupt the regular progression of a student's life in order to make it somehow "better." The goal often is to yield end results that would not have been achieved without the intervention. School leaders have often sanctioned initiatives within their educational walls geared toward combatting dropout rates (Wilkins & Bost, 2016), reducing prejudice and racism (Aboud & Levy, 2013), preventing childhood obesity (Mahmood et al, 2014), and providing COVID-related psychological support (Qian-Hui & Ying, 2020). In addition, a plethora of research has persistently examined the effects of school intervention efforts related to students' interest, entrance, and persistence in science, technology, engineering, and mathematics (STEM) fields (e.g., Burgin et al., 2015; Kitchen et al., 2018).

STEM Defined

Essential to grasping the problem underlying this current study's focus on STEM intervention is how one defines STEM. Having no universal definition for it has likely contributed to confusion in academe and also with findings on how schools in the U.S. and the workforce are faring in the struggle to attract those pursuing STEM careers. Since this dissertation eventually focuses on the effectiveness of a specific intervention program at the center of investigation, the term STEM herein assumes a definition commensurate with the "traditional" meaning of the term. Hence, STEM refers to that which pertains to or is related to mathematics, science, computer science, and engineering (including architecture) but not related to business, statistics, or any of the psychological or social sciences.

An Unstable STEM Workforce

The U.S. Found Lacking

Once the global leader of STEM innovation, the U.S. has fallen terribly behind other nations as related to the percentage of graduates majoring in STEM fields. While no exhaustive list of rankings of percentage of undergraduates majoring in STEM fields by country exists, the United Nations Educational, Scientific, and Cultural Organization (UNESCO) positioned the U.S. outside of the top ten at only 19.6% in 2022 (Buchholz, 2023). It is strongly held among many that the maintenance of a vibrant, well-educated STEM workforce is essential to increase the global competitiveness of U.S.-based industries. To increase such low representation in STEM, several initiatives have been launched across many demographics and at various stages in students' educational journey.

Action Plans for Change

Plans of action for addressing this reported shortage in the STEM workforce vary. Stemming the tide in this regard is a challenge that has remained ongoing, though there has been some progress. Largely, efforts have been intentional to attract various target demographic groups in the hopes of moving the needle in the direction of securing increased delegation in these fields. Strategists have sought unique and calculating methods by which to cultivate STEM interest and encourage entry into related careers.

Strategies over time have included attempts at fostering on-the-job, peer-to-peer mentoring to increase the chances that mentees will obtain promotions (Prendergast et al., 2019) and sometimes for recruiting STEM talent through job fairs and college visits (Rahhal et al., 2020). Major tactics that tend to have yielded more substantial gains have been those that seek to pique and maintain the STEM interest of students much earlier than when they enter the workforce. In this way, a STEM pipeline is created that conceivably establishes in students a STEM-based inquiry and curiosity that predate their working years.

A Unique and Crucial Demographic

Two Key Subpopulations in the STEM Struggle

To ensure contributions and perspectives in STEM from a wide array of the country's talent base, countless efforts have been made to harness strengths from various demographic pockets within society. One key target group in the STEM workforce conversation is that of first-generation (FG) and/or low-income (LI) students. As the first part of the name suggests, none of the first-generation students' parents or guardians have obtained a four-year college degree; although technically, the grandparents may have such a degree, FG status only depends on the educational status of students' households (Covarrubias et al., 2021). LI students are those whose family's taxable income from the year before did not exceed 150% of the Census Bureau-established poverty level; much classification, of course, depends on the size of the family unit (U.S. Department of Education, 2023a).

Though FG and LI student populations are unique in their own rights separately, much attention in STEM has been paid to the intersection of these subpopulations, often referred to as first-generation and low-income (FGLI) students. That FGLI students carry the weight of overcoming two intrinsic odds—being the first generation to attend college *and* being low income—as they navigate college is no trivial matter. Further, their pursuit of STEM arguably makes their journey more formidable—much more so than that of their wealthier peers—and could provide revelatory insight on how best to support them as they strive to reach their career goals. What makes the challenge of meeting the STEM-preparatory needs for this demographic even more daunting, however, is that of identifying and monitoring its own elusive borders, which may morph based on any particular researcher's focus.

Examining Nuance: Putting Shape Around the FGLI Demographic

A common temptation when discussing matters concerning STEM retention is to contextualize the challenges surrounding the dilemma based on race and gender in and of themselves alone. While both demographics may play a role in the struggle to increase representation in such careers, several researchers maintain instead that addressing STEM access gaps with respect to class—within which race and gender are situated—provides a truer reference point when analyzing the issue (e.g., Grineski et al., 2018). Addressing attendees at a town hall hosted by the Asian and Latino Coalition, then-Vice President Joseph Biden made one of his most famous gaffes as pertaining to race and class. Seeking to garner support from the educational community for his presidential run, he declared that "poor kids are just as bright and just as talented as white kids" (Biden, 2019, 0:04). Critics immediately attacked the assumptions lodged in his statement—that all poverty dwellers are minorities while those who are rich and wealthy are non-minorities. Though Biden later issued an apology for the statement, his comments reflect a general sentiment in educational circles and beyond, which tends to conflate race and gender as primary identifiers for being labeled as “at-risk,” especially regarding STEM.

Upon closer scrutiny, a number of scholars suggest that factors not strictly related to race, gender, or other surface markers may serve as more accurate benchmarks against which to gauge STEM readiness, particularly in secondary and postsecondary settings (e.g., Stephens et al., 2014). Expanding this at-risk range arguably allows for a more encompassing critical mass, whose access and entry into STEM may be jeopardized if adequate intervention fails. Included in this underrepresentation are the usual suspects: often-referenced minority groups and women (e.g., Phelan et al., 2017; Xavier-Hall et al., 2022). Such an expanded labeling, however, embraces FGLI students, who garner meager attention in the STEM dialogue. It is a unique demographic in that it represents a cross-section from other well-known demographic categories. However, it also includes representation from students in lesser-known groups, including those in rural public schools—most of whom are non-Hispanic White—immigrants, refugees, students in foster care, and those with disabilities (Harris & Hodges, 2018; Mark & Alexander, 2019; Novak, 2022; Stelter et al., 2021). In sum, the borders of the FGLI community are quite vast, rallying membership from a host of different races, genders, sexual orientations, ages, dependence statuses, and the like. Figure 1 illustrates various lenses—not exhaustive—through which the FGLI demographic can be seen within the borders of undergraduate institutions in the U.S. (Hamilton, 2023).

Implications for FGLI Students

The astute researcher notes, then, that the FGLI demographic is a diverse, complex entity. It is not categorized solely by race, gender, municipality, age, immigration or refugee status, disability, or any other surface-defining attributes. Therein

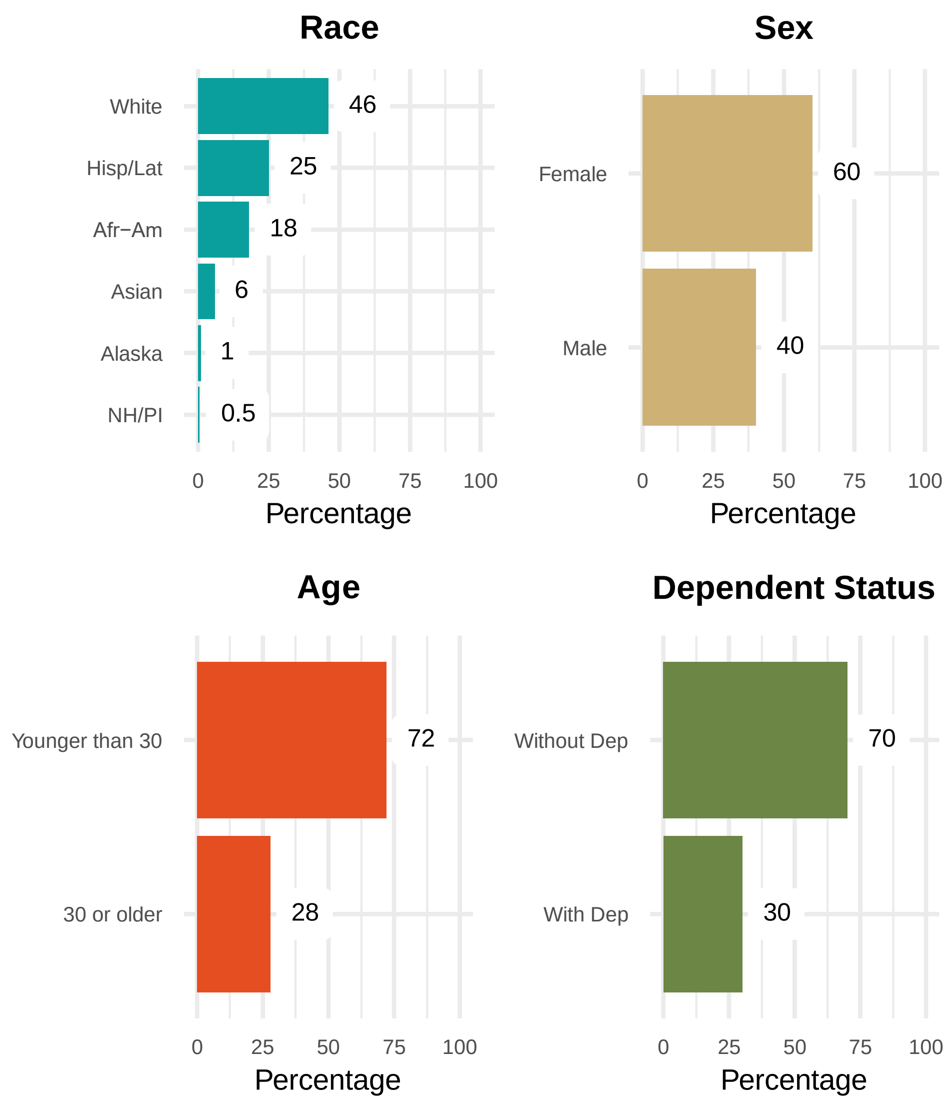


Figure 1. *U.S. Undergraduate First-Generation, Low-Income Students by Select Characteristics*

Note. Interpreted from Forbes Advisor. See reference for Hamilton, 2023.

lies the challenge in meeting the needs of such students with respect to STEM support or to college success in general. Its amorphous, multifaceted identity has led researchers to deem it difficult to pinpoint and track such a population, frequently dubbing it as invisible (Peña et al., 2022) and forgotten (Hirudayaraj & McLean, 2018). Consequently, challenges remain concerning providing such a demographic with the support it needs to navigate through college, especially in STEM fields. If leveraged appropriately, such consistency of aid, some assert, would lead to a more inclusive and competitive America, tapping into a gold mine of STEM creativity and leveling the economic playing fields since such careers tend to be rather lucrative (Bettencourt et al., 2020).

The Problem

By 2029, the number of STEM-focused careers is expected to increase by 10%, a growth rate that significantly outdistances that for other fields (Bureau of Labor Statistics, 2021). As emergent technologies become more and more a part of day-to-day life and as medical challenges like COVID-19 requires persistent monitoring and vaccine tweaking, the need for STEM-based expertise will continue to remain at an all-time high. Despite how promising the field is, however, STEM supply is struggling to keep up with STEM demand, according to some. While some scholars assert that the alleged shortage of STEM talent is overexaggerated and grossly untrue (Salzman & Douglas, 2022), others maintain that a huge share of STEM-related jobs still remain unfilled, citing downward trends in the number of U.S. students who major in such fields, especially among underserved populations (Beamer, 2023).

Fertile Ground: Tapping into Prospective FGLI Talent

While no consensus pervades concerning whether such a supply shortage exists, very few disagree with the fact that a significantly untapped pool base of STEM talent exists within the FGLI community. The community's potential contribution in this area is not to be ignored, particularly based on the realities that surround its presence on the college and university scene. Pointedly, its lackluster postsecondary presence in STEM points toward a rich opportunity to harness the potential talent resources to positively impact representation within said fields.

Relatively recent statistics reveal that roughly 70% of those enrolled in colleges and universities in the U.S. represent those from continuing-generation (CG) households; FGLI students comprise the remaining 30% (Ceyhan et al., 2019). Of this bunch, only a meager 27% go on to finish the degree within four years (Whitley et al., 2018). In more practical terms, for every 100 enrolled college students, 30 of them come from first-generation, low-income households. Of these 30, only approximate eight finish the degree within a four-year period, translating into an attrition rate slightly under three-quarters. Figure 2 illustrates these comparative relationships and numbers.

On a different front, data reveal a bittersweet reality concerning STEM enrollment among FGLI students in U.S. colleges and universities. While FGLI students comprise only 20% of STEM enrollment in U.S. college and universities (Peña et al., 2022), they maintain a staggering finish rate close to 75% (Bettencourt et al., 2020). Essentially, for every 100 enrolled college students who major in STEM, 20 of them come from first-generation, low-income households. Of these, roughly 15 finish the degree with said

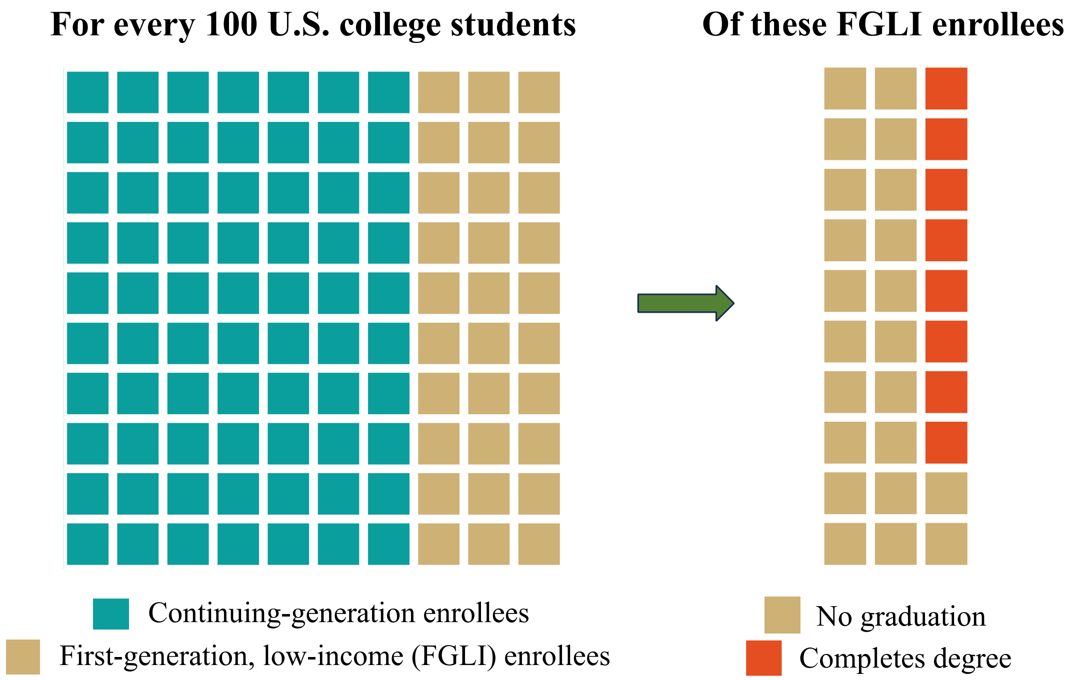


Figure 2. *U.S. College Enrollment: Continuing-Generation and First-Generation, Low-Income Enrollees*

STEM major within a four-year period. With such a perceived rate of success, by some standards, increasing this FGLI student pool may arguably do its fair share in contributing to STEM career shortages, given that the attrition rate is rather low. Figure 3 illustrates these comparative relationships and numbers with regard to STEM.

Situating the Current Study

Given these realities, this dissertation explores a number of research questions that examine the effectiveness of a university-run STEM intervention program for FGLI high-schoolers. The study initially discusses the framework that supports the study. Setting this foundation will guide the flow of the study's methodology and provide boundaries for the study's scope. Finally, the work examines one of these university-hosted programs, the Upward Bound Math and Science Program, unearthing any existing

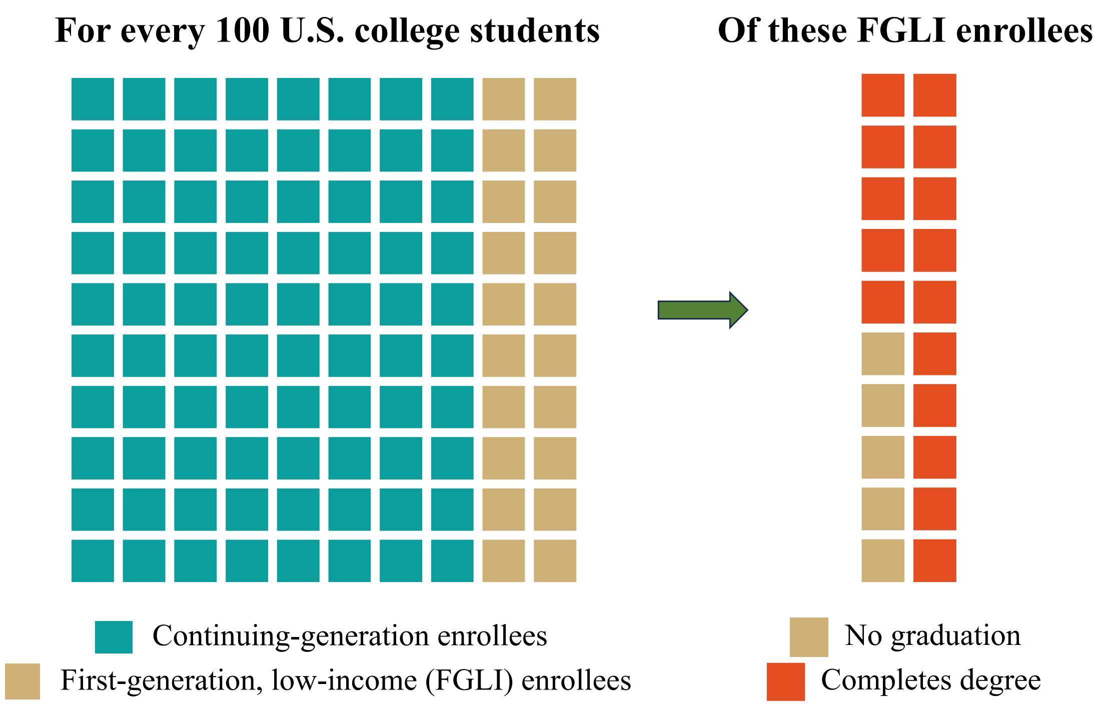


Figure 3. *U.S. STEM College Enrollment: Continuing-Generation and First-Generation, Low-Income Enrollees*

evidence that involves the program's possible success or failure with students. Guided by what the research reveals about the program, the purpose of the dissertation arises, and the research questions emerge, along with rationale for why these questions are worthy of investigation.

CHAPTER 2

A REVIEW OF THE LITERATURE

Primarily, this literature review explores existing literature central to a history of STEM in the U.S. and discusses STEM-intervention programs (SIPs) and their claims of effectiveness. The review initially provides a brief history of STEM on a rough continuum from the late nineteenth century. Next, SIP effectiveness is discussed at various academic levels—from elementary to high school. The review especially targets SIPs at the high school level, providing justification for why the focus at that level makes sense for this study. The review then considers the level-appropriate outcome of students' attainment of a rigorous course of study and enrollment into advanced math courses as proximal measures of success, giving attention to several overarching variables that tend to influence the stated outcome. Since the crux of this study centers on how specific SIP attributes associate with the dependent variables, the lion's share of the review looks intensely at how independent variables connect with the two stated measures; namely, the review looks closely at which salient components within an SIP are key.

A History of STEM Intervention in the U.S.: Key Moments and Legislation

A cursory history of STEM intervention reveals several observations, including key moments contributing to its development and legislative twists and turns. Whether STEM's aim was to assist agrarian science or to increase postsecondary degree rates, its common thread over time has been to act as a measure to create social justice and to strengthen the core of economic leadership in the U.S. By making access into these highly specialized fields possible for all students, the gap between the economic haves and have-nots shrinks, at least in theory.

Early Roots

STEM intervention in education is not a new phenomenon. It can be traced back to as early as the mid-nineteenth century. The Morrill Acts of 1862 set aside federal dollars for colleges that offered agricultural and mechanical studies; deemed as "land-grant institutions," in which states were offered land to establish public universities devoted to agrarian and military science, these hubs would provide students educational opportunities for economic stabilization and footing during a bitter and intense Civil War currently plaguing the country (Johnson, 2011). In fact, although this first of the Morrill Acts was not established to assist any particular ethnic group, the second one—The Morrill Act of 1890—was enacted to deliberately found and fund post-war institutions that enrolled Blacks. Because of staunch segregation in the South, these land-grant funds became a tacit social contract between the U.S. and some of its marginalized citizenry, leading to the establishment of several historical Black colleges and universities (HBCUs)—dubbed the "1890 schools"—including Florida Agricultural and Mechanical (A&M) University, Alabama A&M University, and North Carolina Agricultural and Technical (A&T) State University (Brown & Davis, 2001).

World War II, the Race to Space, and NASA

Science and engineering's footprint since these Acts became primarily evident in business circles, being marketed as a bridge for boosting the economy through inventions and innovations, such as cars, light bulbs, and other technologies (White, 2014). In the early to mid-1900s, however, the focus of these intervention types morphed into mechanisms to bolster and reinforce a sense of home-based national security amid global threat. To equip the U.S. with the technological know-how needed to build machines of war, scientists and engineers were called upon to carry out such tasks during World War II (Ritz and Fan, 2015). In addition, this same cadre of thought-leaders assisted the country in building economies back to where they were before the war.

Further, when Sputniks I and II were launched in 1957, Russia was placed at the forefront of all nations of the world with respect to science and innovation, making an already Cold War between the U.S. and Russia even colder. Serving as a wake-up call to the rest of the scientific global community, the U.S.'s loss in this space race contributed significantly to a belief that the U.S. had to safeguard its people from other countries' militaristic threats, re-prioritize its science curriculum, and inspire a generation to pursue technological- and engineering-related careers (Mohr-Schroeder et al., 2015). These factors became key in placing the country on a trajectory that placed science-based thought in the forefront of its national agenda. To boot, President Eisenhower's creation of the National Aeronautics and Space Administration (NASA) in 1958 directly reflected this robust re-prioritization, amplifying science interest on a more national level (Hayden et al., 2017).

The Economic Opportunity Act of 1964

In the mid-1960s, the establishment of a conglomerate of domestic policy initiatives headed by President Lyndon B. Johnson attempted to address home-grown shortcomings related to poverty, racism, and educational lack. Although the Vietnam War was still ongoing at the time, much of the warspeak was on the country's in-house War on Poverty. The timing was ripe to create programs that would target the country's social and educational sore spots, hopefully leading to a wide array of solutions. Along with forging the Civil Rights Act of 1964, the Voting Rights Act of 1965, and the Social Security Amendments of 1965, President Johnson established the Economic Opportunity Act (EOA) of 1964, all components of The Great Society, one of the most extensive social reform plans in modern U.S. history (Bailey & Duquette, 2014).

Creation of STEM Councils

The turn of the twenty-first century witnessed more federal and private resources used to support STEM campaigns. Janet Napolitano, the governor of Arizona at the time, was instrumental in pushing these initiatives into educational spaces for her particular state. Having strong foci in mathematics and science, these efforts were framed by an urgency to keep the country's children from falling behind other countries, especially "in measures of postsecondary degree rates and international test score comparisons in mathematics and reading" (Suter & Camilli, 2018, p. 54). As Arizona led the way in making strides to address this conundrum, other states followed suit, creating STEM councils, developed statewide strategic plans whose mission included some degree of bolstering student interest in STEM, which would hopefully lead to key careers to strengthen the state's economy.

Educate to Innovate

In 2009, a President Obama-launched initiative made its way onto the national scene. Dubbed the Educate to Innovate program, its mission was not particularly surprising to many. Similar to other STEM-related interventions in the country, this initiative set the goal of raising the levels of excellence in science and mathematics to a new level of competitiveness. Having foci spreading across grade levels, the initiative represented an attempt to give the U.S. a technical “shot in the arm,” thus strengthening its science and math base across the country. From airing Sesame Street episodes that would explore ideas of the environment and nature to forging educational opportunities related to STEM-based video games to instituting National Lab Day, these proposals sought to get the U.S. excited again about education and specifically STEM-based education (Pienta, 2010).

The American Recovery and Reinvestment Act and Race to the Top

Though aware of federal limitations within educational spheres, an eager Obama continued to poise the country to lead in the global economy by pushing for legislation to tackle educational inequities. Such efforts resulted in successful ratification of the American Recovery and Reinvestment Act (ARRA), whose Race to the Top initiative sought to assist states and school districts to become competitive conduits for increased K–12 student success (Vinovskis, 2022). This multibillion-dollar grant allowed states to apply for and compete for funds to systematically improve teaching and learning in America’s schools; although not an initiative solely designed to bolster STEM in education, the measure included as part of its competitive selection criteria (i.e., Priority 2) points for state applications that forged an “[e]mphasis on [s]cience, [t]echnology, [e]ngineering, and [m]athematics” (DOE, 2009, p. 3).

STEM Education Act of 2015

Comprised of four sections, the STEM Education Act of 2015 sought to do its part in keeping STEM-related education at the center of U.S. thought. Primarily, the Act added the field of computer science to the National Science Foundation’s functioning definition of STEM (Zouda, 2018). Hitherto, computer science existed as a viable, yet separate, academic discipline. As the country became more dependent on computers and computer-based programming in citizens' daily life, emphases on preparing students to excel in such fields became paramount. With more reliance on companies like highly programmed-based Google and a global shift toward the increased use of apps and social media giants like Facebook and Instagram, adding computer science to the STEM definition signaled an appreciation and urgency for training students to understand the unique language undergirding such a burgeoning field. The legislation also gave the National Science Foundation continued responsibility in the awarding of merit-based, competitive grants focused on research and development tied to improving STEM learning outcomes (STEM Education Act, 2015).

The INSPIRE Women Act

A constant issue in the STEM struggle is the access for women in the field. In 2017, Virginia's Representative Barbara Comstock introduced the Inspiring the Next Space Pioneers, Innovators, Researchers, and Explorers (INSPIRE) Women Act. Though the Act consists of several sections, the Trump-backed stratagem primarily obliges NASA to urge women and girls to study STEM, pursue aerospace-based careers, and continue to push the country's science and space agenda (INSPIRE Act, 2019). This piece of legislation is notable because it represents the first effort to mitigate low STEM representation numbers by specifically targeting women in relation to the aerospace industry.

An Overview of STEM-Intervention Programs

SIPs have become major fixtures on the educational scene and show no signs of retreat. Such programs are as much a part of the learning ethos in schools as the school's basic curriculum itself. To the surprise of many, initiatives regarding the development of SIPs in educational settings not only address notions of workforce dynamics, but they also become instrumental in serving as programmatic tools for righting social wrongs. District and local school leadership remains particularly deliberate in sanctioning SIPs within school walls as vehicles for combatting social injustice. When certain groups—women, minorities, and the poor—continue to be excluded from having equal access into STEM fields, there linger a sense of inequitable distribution of society's resources and unfair advantage (Leggon & Gaines, 2017). Hence, experiences that support meaningful engagement so that all students can have access to STEM not only tend to result in better-equipped students on the job but also in a more empowered global citizenry (2017).

SIPs have maintained an undeniable presence across all levels of the educational landscape, serving various subpopulations within the scholarly community and assuming a variety of formats. At the elementary, middle, and high school levels, SIPs have been instrumental in sowing seeds of scientific curiosity, fostering scientific inquiry, impacting student STEM perceptions and attitudes, and cultivating a sense of STEM self-efficacy (Leas et al., 2017; Ahmad & Siew, 2021; Roberts et al., 2018; Phelan et al., 2017). Intervention efforts in colleges and graduate schools frequently focus on strengthening the quality of student STEM research and accentuating the role of mentorship as students prepare to transition into the workforce (Rodríguez et al., 2018; Williams et al., 2022).

Countless SIPs focus their efforts on serving a variety of subgroups in order to effect change within the same; most popular among these are programs aimed at offering intervention support by gender, by ethnicity, and by socio-economic status (Falco et al., 2019; Stevens et al., 2017; Dietrichson et al., 2017). Lesser-known SIPs are those that seek to assist veterans, those with disabilities, and members of the LGBTQ+ community, the latter of which has given rise to such nomenclature as Out in Science, Technology, Engineering, and Mathematics or oSTEM (Goldberg et al., 2015; Lindsay et al., 2019; Wong, 2018). Depending on available resources and grade level, SIPs can vary in their format, offering residential or nonresidential services, and also in their duration, where students participate during the summer, during the school year, or after school (Ikuma et al., 2019; McCoy & Winkle-Wagner, 2015). In all, SIPs have attained an appreciable level of notoriety in educational circles and claim to offer much by way of influencing outcomes related to STEM.

A Look at the Effectiveness of SIPs

Factors that associate themselves with SIP-intervention effectiveness depend on students' developmental level. As students migrate through the educational system, they grow and change. Not surprisingly, so do strategies and foci regarding what is deemed effective with respect to what influences their STEM interest and maturation. At the elementary school level, intervention methods relate to the extent to which lessons are inquiry based and also to adequate STEM teacher preparation. STEM efficiency in middle school is linked to how students view STEM in relation to their community and the degree to which they are engaged as citizens.

Elementary School

As one might surmise, STEM intervention at the elementary school level does much to establish conceptual understanding of science and its purpose; some researchers posit that, at this pivotal juncture, it awakens a curiosity that is needed to egg students along on their academic journey with an eye toward the sciences. Piquing students'

STEM interest during elementary years often generates needful seeds of inquiry that provide strong bases for growth in target fields (Graves et al., 2016; Ching et al., 2019); further, interceding throughout these formative years do well to maintain science interest among little girls (Sullivan & Bers, 2018). Failure to take seriously the role of STEM intervention at this level, some say, squashes the motivation of children—irrespective of race, gender, or class—as it relates to feeling a belonging to such fields. Pratt (2007) warns that creativity, curiosity, and verve can easily wane if not nurtured in elementary grades.

Several researchers have stressed the urgency of inquiry-based learning as well as teacher preparation as they link to effective STEM realities for elementary schoolers (Cotabish et al., 2013; Robinson et al., 2014; Nadelson et al., 2010; Isik-Ercan, 2020). Reaching students effectively at this level concerning STEM, many find, centers around how STEM is taught, methods employed while doing so, and the degree to which teachers are professionally developed. For example, Cotabish et al. (2013) found that intervention proved efficient when curriculum forged inquiry- or problem-based units of instruction. Use of the STEM starters curriculum, specifically designed for elementary school students, required learners to focus less on rote memorization (i.e., low cognitive demand) and more on the lessons' numerous overarching concepts like stating examples, non-examples, categorizing, and generalizing (i.e., high cognitive demand). Further, intervention that reflected adequate teacher training, which focused on science content and delivery contributed to effectiveness at this level; such preparation included teachers' embodying the role of students and immersing themselves in level-appropriate technology for each lesson (2013).

Middle School

Although inquiry-based instruction and teacher preparation occupy their place with respect to effective STEM intervention among middle schoolers, much more emphasis at this level is placed on efforts that reinforce a sense of collectivism and which relate to STEM's existence in a larger social, civic, and environmental context (Gray et al., 2020; Smalley & Kaminski, 2017; Condon & Wichowsky, 2018; Burrows et al., 2018; Paige et al., 2015). As STEM identity at this level tends to parallel students' community awareness and civic responsibility, STEM intervention efforts that occur within a context which supports a sense of communalism tend to maintain middle school interest in such fields. Gray et al. (2020) found that STEM lessons that were anchored in real-life connections to the students' own community helped retain students' STEM interest, particularly with engaging Black and Latinx middle school students. In another study, STEM intervention efforts that focused primarily on exposing middle school girls to female scientists did not significantly increase the girls' STEM interest (Smalley & Kaminski, 2017). Although study results did not imply that the impact of gender on student interest should be ignored, they do reveal the limited nature it has at this grade level. Results of the study seem to confirm

> that during early adolescence, valuing communal goals, like working with and helping others, may possibly be a more influential factor than gender category membership on STEM interest . . . [E]mphasizing communal goals in this population may be a more effective and practical way to increase STEM interest than more traditional interventions that emphasize stereotype-disconfirming exemplars and femininity. (p. 3201)

This notion of STEM interest tied to a purpose linked to one's community is key to nurturing STEM seeds to students at the middle school level.

Relatedly, incorporating a citizen science approach in the teaching of science in middle grades has contributed to students' enhanced science literacy and sustained STEM interest (Paige et al., 2015). In such a methodology, students migrate from drawing upon the basic scientific method to arrive at scientific knowledge to garnering scientific knowledge in a more constructivist manner; students participate in knowledge acquisition not only by "doing" science but by doing it in a manner that connects them as student-citizens to the natural world around them. Condon and Wichowsky (2018) found that integrating a joint inquiry-based, science- and civics-laden curriculum, middle schoolers' engagement in both STEM and civics increased. Their implementation of the STEMhero software allowed students to track and analyze water meter readings from their own homes with hopes of increasing their own water efficiency. The study suggested that such a format contributed notably to the development of students as "'citizen-scientists' who [were] excited about further study in STEM and civically empowered to deliberate on science-based social and community concerns" (p. 198).

Paige et al. (2015), for example, developed instructional models aimed at constructing kitchen-gardens with a cluster of teachers and students in South Australia, in which food, how to grow it, and cooking healthily were key topics of study. Primary tasks included: 1) creating composting systems; 2) raising seedlings; 3) establishing a garden; and 4) investigating soil salinity (2015). Not only had students made a garden within the borders of a public school, but they had also created adjacent walking trails. The study maintains that this approach of connecting middle school student-citizens to the natural world offers a meaningful context for them to learn about and bolsters continued interest in STEM (2015). Still, other studies likewise support such a notion of strengthening middle school students' STEM interest by relying on an educational model that links scientific learning to the world that intersects with their very own (Hiller & Kitsantas, 2022; Anwar et al., 2022; Rodriguez et al., 2019).

High School

In the context of this dissertation, literature surrounding the effectiveness of SIPs at the high school level becomes drastically vital. As the major focus of the current study will be involved with analyzing the effects of STEM intervention among the FGLI population, it becomes crucial to consider numerous angles from which to explore what makes such intervention efforts efficient or not. Specifically, justification is offered for why a refined look at intervention at the high school level makes sense, considering the research questions that will guide this study. With an eye toward the study's outcome variables—obtaining a rigorous course of study and taking advanced math courses in high school—the review briefly considers a few high school-related factors contributing to such variables, examining extensively the SIP characteristics linked to intervention efficacy. Particularly, when analyzing the effectiveness of high school SIPs, the focus of the review is limited to a discussion of college- or university-run SIPs.

Why Focusing on High School is Key

Investigating STEM intervention efforts in high school becomes pivotal in the equation of student STEM success in college. Though STEM foundations established in elementary and middle schools serve integral purposes, intervention efforts explored during students' high school tenure often determine whether students achieve a rigorous course of study or complete advanced math courses. With regard to increasing opportunities for disadvantaged or underrepresented students, STEM intervention at this level proves pivotal, as having a rigorous set of courses and completing advanced math courses establish the necessary foundation for postsecondary STEM success.

Notably, an independent study found that students who take precalculus and calculus courses in high school are almost six times as likely to reach math college-readiness standards when compared to students who do not take similar math courses; likewise, students who take biology, physics and chemistry in high school are almost three times as likely to reach science college-readiness standards when compared to students who do not take similar science courses (American College Testing, 2019). Such results have tremendous implications for those who lack adequate access to such courses because of possible structural barriers tied to gender, race, or other socio-economic background. Mitigating these systemic challenges at the high school level, though a tall order, is crucial to opening many students' pathways to enrolling in such courses and declaring STEM majors.

Measurable Outcomes Indicating High School Interest in STEM

Proper analyses of high school SIPs address measurable outcomes that are reasonable and research-based, given the educational level of the student at the time of intervention. This variable of success can take on various forms, depending on where students are in their scholastic life. Success for undergraduates who are beneficiaries of SIP assistance is often measured by whether students successfully graduate with a STEM major and perhaps pursue an advanced STEM degree (Maton et al., 2016; Ikuma et al., 2019; Momoh, 2014). For undergraduates, these particular SIP outcomes are of a more proximal nature; for high schoolers, however, these same outcomes become more distal, linked primarily to students' actual experiences during the college years themselves

(Bottia et al., 2015). Alluded to earlier, more level-appropriate outcomes for high schoolers benefitting from SIP exposure tend to focus on whether or not they obtain a rigorous course of study (Sadler et al., 2014; Wai et al., 2010) or take advanced math courses in high school (Warne et al., 2019). These measures tend to be unique indicators that signify STEM interest.

A Rigorous Course of Study as a Measurable Outcome

A retrospective study conducted by Sadler et al. (2014) found “evidence that students who take one or two years of calculus, a second year of chemistry, and one or two years of physics in high school exhibit a significantly higher STEM career interest, as a group, than do students who do not take these courses” (p. 10). The study was conducted with a group of first-year students enrolled in two- or four-year institutions. The likely linkage between enrollment in rigorous courses and students’ interest in STEM is buttressed by the notion of “educational dose,” which suggests that an increased amount of educational “medicine” prescribed at the right time and with the right mix will yield desired, healthy results (Wai et al, 2010, p. 861). A transcript reflecting a rigorous course of study further shows that students have taken non-STEM courses to round out their educational journey, including AP literature, AP Statistics, and, more recently, AP Economics (Ogut & Circi, 2023; Eisenhart & Weis, 2022; Owen, 2024). According to some, this academic mixture works well to expose students to the appropriate amount of material and content, which reinforces in them a sense of competence and self-efficacy when grappling with STEM challenges at the postsecondary level. Students whose courses reflect the right amount of academic rigor by the time they finish high school are, in theory, more likely to pursue STEM majors in college and, later, STEM careers. Several studies corroborate such correlational findings (e.g., Means et al, 2016).

Advanced Math Course Enrollment as a Measurable Outcome

When considering the association between advanced courses taken and STEM interest, one focuses primarily on mathematics since it is often the gateway subject necessary for all STEM majors (Warne et al., 2019). Studies that track correlation between high school students' enrollment in advanced math courses and STEM interest offer mixed results. Several studies indicate that no significant association exists between the two variables (Sadler et al., 2014; Chen et al., 2023). Other studies support results showing a significant relationship between both quantities (Gottfried & Bozick, 2016; Green & Sanderson, 2017). Warne et al. (2019) seemingly back both positions, as findings in their study conclude that taking such courses, in general, showed insignificant correlation with students' STEM interest; however, results did demonstrate specifically that students taking AP Calculus showed pronounced interest in engineering and mathematics. Wang's findings imply that increased high school students' interest in pursuing STEM fields of study could be a response to early introduction and exposure to math-related courses (2013).

Characteristics Tied to Rigorous Courses and Advanced Math Course Enrollment

High school characteristics, student characteristics, and characteristics of the SIP itself have a marked association with high school students' attainment of a rigorous course of study and enrollment in advanced math courses. In this discussion, one briefly considers the first two characteristics and their role; since the focus of the dissertation is primarily concerned with SIPs and their influence, however, the variable regarding attributes of the SIP is discussed in more detail.

High School Characteristics

Among the variables linked to students' enrollment in advanced math courses is that of high school characteristics. In one sense, the linkage is very simple and direct. If high schools do not offer certain courses like trigonometry or calculus, it is unlikely that students will enroll in them. Indirectly, it exists as an antecedent in the sense that it provides the general foundation upon which students build as they navigate through the SIP. Even though SIPs may service certain target schools in their area, these very same schools also possess certain qualities that distinguish them from those within their target cohort. This tends to produce students who begin SIP participation at varying levels of competence and expertise, which can contribute to how effective an SIP can be for specific students and associate with whether students cultivate an interest in STEM. Among these high school characteristics that are associated with the two outcome variables are availability and access, the school's racial composition, and the school's teacher quality and competence.

Availability and Access. First, schools that offer students access to rigorous courses of study and advanced math tend to witness more students that go on to pursue postsecondary STEM aspirations (Gottfried & Bozick, 2016). Relatedly, Wang (2013) found that twelfth-grade students' exposure to upper-level mathematics and science courses directly affects their intent to major in STEM and obtain degrees in those fields. Zuniga et al. (2005) found that high-achieving Hispanic students who were placed in lower-level science courses were unlikely to enroll in college-preparatory science classes whereas low-achieving White students at the exact same school who were placed in the upper-level science courses were likely to enroll in college-preparatory science classes, thus bolstering their success in science.

One could argue that this same logic is not out of the question for mathematics courses. In many high schools—especially rural ones—upper-level courses are not offered. In this event, students retain the option of exploring various alternatives to fill in the STEM gaps and keep access to such courses possible including taking an online AP math course; enrolling in dual-enrollment courses at a local college (virtual or in person); and taking a private online test prep course to potentially pass AP exams and earn college credit (Claybourn, 2022).

Racial Composition. Although the availability of rigorous and advanced math courses is in direct relation to students' decisions to enroll in them, a different challenge emerges when such courses are indeed accessible for any student to take. A high school's student racial composition often plays a role in whether or not students are actually enrolled in these academically rigorous courses. Many times, it does not merely boil down to student choice as it relates to taking these courses, specifically for minorities. Often, these students do not have the luxury of choosing these courses for a number of reasons, including low teacher and counselor expectations and low-to-no rigorous course availability at certain schools. Especially in zones where academic resources are low, this is the reality. If courses are not offered, then courses cannot be taken. Only for a select group of informed and motivated students who fall in this category, courses may be taken at another school or approved online venue, making success in college still a viable possibility.

Partly rooted in various forms of tracking, the idea of unbalanced representation of minorities in these courses is often reflected in systemic, within-school segregation (Mickelson, 2001). Time and again, students are steered into course selections that indicate teachers' preconceived notions of what said students can or cannot accomplish academically. By the time many minority students reach high school, they may have already begun following a less rigorous academic path, especially in STEM, translating to a decreased likelihood of enrollment in these courses when the appropriate time arrives. Very frequently, then, the issue is not solely that minorities are opting out of taking advanced courses because of a lack of interest; often, they do not enroll because they lack the urging and support to take them, which can alter the direction of their educational plight (Glennie et al., 2019). What's more, even before entering high school, many of them have fallen prey to the lack of availability of preparatory courses like algebra at their respective middle schools. This reality often initiates an undeniable domino effect from which it becomes difficult for students to recover.

Teacher Quality and Competence. Third, teacher quality and effectiveness are associated with students' decisions to take advanced courses. Experiencing teachers who have the appropriate certification and who stress conceptual understanding positively associates with students' future college plans in STEM (Ekmecki & Serrano, 2022). Further, teachers who leverage strategies specific to a subgroup's learning culture tend to influence that subgroup's propensity to pursue STEM after high school. Moller et al. (2015) discovered that there was an increased probability that Latinx students pursued STEM in college when teachers taught in collaborative, nurturing, and mentoring environments (i.e., ethic of care); this tended to show that effective teachers were those who made strides to consider the "whole" student even when teaching content-specific material. You (2013) found that, among other contributors, quality teachers are influential to Black and Latinx students' mathematics trajectory into postsecondary life, irrespective of students' background or demography. In addition, Ma and Liu (2015) seconded that taking advanced STEM-preparatory courses in high school and having higher SAT scores were a function of school course offerings and teacher quality.

Student Characteristics

Associated, too, with students' propensity to take advanced courses in high school are characteristics related specifically to students themselves. Several of these characteristics have a moderate to fairly strong association with regard to whether students enroll in said courses. Students' gender, their parental influence, and their own behavior become key in how and if they choose to enroll in these courses, which would increase the likelihood of their choice to pursue STEM majors in college and, later, pursue STEM careers.

Gender. According to the Department of Education's Civil Rights Data Collection numbers, data reveal less disparity than has been historically noted concerning AP STEM enrollment by gender. Latest data trends suggest that there is more balance between males and females in course participation. Female AP math enrollment in high schools across the nation during the 2017–2018 academic year reflects an upward turn, having risen to 50.34%, narrowly besting that of their male counterparts; female AP science enrollment has increased as well, hovering at 52.8% (OCR, n.d.). In Pennsylvania, gender margins remain close but not as tight as national ones. Male AP math enrollment in the state resides at 50.89%, slightly edging out female representation, while female AP science enrollment in the state, reaching 53.89%, outdistances male enrollment (OCR, n.d.). All of these statistical data were state and national estimations between 2017 and 2018. Though such data fail to delineate between the sciences (e.g., biology, chemistry, physics), one cannot deny the reality that the gap between males and females taking AP STEM courses, nationally and in Pennsylvania, is not particularly appreciable.

Arguably, there exists an association with high school females' social circle as it relates to STEM interest; according to Raabe et al. (2019), high school females in Sweden tended to retain their STEM penchant when their female peers also had STEM interests. Often, the STEM pipeline for secondary females becomes a social pipeline, which contributes to the traditionally reported widening of the STEM gender gap since high school females, on average, seemed to have preferred STEM to a lesser degree than their male counterparts (Saw et al., 2018). As female peers continue to see themselves as viable participants in a once-male-dominated field of interest (i.e., self-efficacy realization) and as STEM itself becomes less stigmatized—especially with the thriving of social media and its associated ties to computer science—the gender gap with respect to enrollment in advanced courses continues to remain modest (Saw, 2020).

Socioeconomic Status and Parental Influence. Socioeconomic status (SES) and parental influence work hand in hand in an association with whether or not students enroll in rigorous courses. In their study, Mau and Li (2018) found that "students who aspired to STEM careers reported significantly higher SES and parental involvement than did students who aspired to non-STEM careers" (p. 251). In the same vein, Plasman et al. (2021) found that students' parents' STEM careers, along with the students' family income level, associate with students' STEM pursuit. Parents who work in STEM become able to provide a perspective about the field to their children that they may not have been privy to otherwise. In addition to taking STEM preparatory courses, students receive the added benefit of possibly living in an environment in which STEM thrives on a daily basis. This makes student pursuit of STEM more likely.

Much of the research on the effects of SES on student academic achievement has been corroborated ad nauseum. Associations between the two variables have been found to be constant and long standing across disciplines, especially in STEM. Low SES tends to associate well with lower results, not because low income equals low intelligence. Berry et al. (2013) assert that neighborhoods and their schools are typically segregated based on SES, often translating into fewer resources, poorer teacher quality, and uneven access to rigorous and advanced courses, on average. In contrast, students who attend schools in more resourced communities tend to reap the advantages that come along with such, including cutting-edge resources, "better" teaching quality, and relatively equal access to advanced courses. Ultimately, according to Gonzalez et al. (2020), "[t]he net effect of this reality is the reproduction of the inherently unjust social system in which we live" (p. 458), creating a never-ending, SES-based merry-go-round of inequality.

Student Perception and Behavior. Student perception and behavior are inextricably bound to one's decision to enroll in advanced courses. Such behaviors include how much effort and time students dedicate to their own studies, involvement with peers, and interaction with STEM teachers or faculty (Xu, 2018). In addition, overall student attitudes, precursors to student behavior, are key ingredients in stated enrollment. Pointedly, a number of researchers have applied and extended Ajzen's theory of planned behavior (TPB) model to students' STEM-related choices. Taylor (2015) called upon TPB to highlight students' attitudes and behavior in the U.K., which tended to predict the likelihood that they would enroll in physics classes. Other researchers used the same model to reach similar predictive conclusions regarding students' resolve to enroll in chemistry-related courses (Crawley & Koballa, 1992; Ong et al., 2022) and mathematics course grades (Burrus & Moore, 2016).

Research data also suggest the converse. When students harbor negative perceptions of science and mathematics, enrollment in such courses lessens. High levels of science and mathematics anxiety tend to associate with lower enrollment in science and mathematics courses, despite typical demographic markers like race and gender; though there is no certain causal relationship, STEM anxiety seems to show indication of student hesitancy in taking courses that might pave the way to developing further STEM interest (e.g., Megreya & Al-Emadi, 2023).

University-Run High School SIP Characteristics

In addition to school characteristics and student characteristics, attributes of SIPs themselves are crucial in their role pertaining to student enrollment in rigorous courses in high school. Arguably, this variable holds considerable sway with respect to students' outcomes related to taking such courses. This portion of the review highlights what the literature offers regarding university-run STEM high school SIPs over the last decade. Contributing literature showcases programs of varying durations, ethnic foci, gender, and cohort sizes. The earliest of these university-hosted SIPs arose in 1958 when Texas Technological College (now Texas Tech University) offered a summer physics course experience for a cohort of gifted high school students; it was supported by the Fund for the Advancement of Education (Day, 1959). One may astutely observe that the formation of this and other SIPs during this time dovetails with the 1957 launch of Sputnik, suggesting a renewed urgency in the U.S. to become a formidable player on the STEM scene (Roberts & Wassersug, 2009).

Though each university-hosted SIP differs in unique ways, the literature reveals clusters of unifying components that aid in making STEM intervention efficacious for students. Several program features contribute to students' trajectory in their STEM quest. Among such attributes are: 1) how engaging and innovative the program curriculum is; 2) how strategic students' relationships are with program professionals (i.e., faculty); 3) how well the program fosters a sense of self-efficacy among students; and 4) how the program assists students and parents with navigating waters tangential to their STEM pursuit but critical to their collegiate journey and beyond.

Forging an Innovative Curriculum. Central to almost all literature discussing SIPs is an awareness of the importance of exposing students to curriculum that is engaging and meaningful (Zhou, 2020; Nite et al., 2014; Lane et al., 2020; Groen et al, 2015; Momoh et al., 2014; Patel et al., 2021; Eeds et al., 2014; Huyer et al., 2018). Basic lecturing featuring an instructor's robotic chalk-and-talk sessions has become more and more passé and is not highlighted in the literature as a factor in encouraging students to gain interest or persist in STEM. Rather, instruction that tends to be more hands-on, mastery based, and focused on developing capstone projects contribute to sustaining students' curiosity in their STEM pursuit.

Hands-On Instruction. Although such programs may offer some instruction by way of traditional teaching and lecturing, research purports that hands-on learning contributes hugely to students' STEM attitudes and interest (Zhou, 2020). Also known as project-based learning (PBL), hands-on learning provides students the chance to learn through authentic experience rather than listening to a typical lecture. In a study by Nite et al. (2014), high school students were exposed to PBLs throughout a two-week summer engineering camp at a Research I university. One key finding was students' increased interest in STEM because of the PBL-centric instruction. Further, Salto et al. (2014) maintained that participant groups herald hands-on research as the most valuable component of the SIP at Loma Linda University, citing its link to students' increased motivation to pursue a science career.

Often, these hands-on experiences occur outside of the normal four walls of a classroom, situating students in an environment where "real life" learning transpires. Further, using real-life, hands-on learning to teach courses like prealgebra and algebra may keep students' interest piqued and reduce attrition in the pipeline to taking rigorous courses later in high school (Gottfried & Bozick, 2016). Whether in a laboratory or at an actual job site, learning within an authentic, PBL-inspired STEM context tends to make enrollment in such courses more probable.

Mastery-Based Concentration. Some studies show that providing an atmosphere where students are allowed to demonstrate mastery of a concept, without the added pressure of time, can help stave off anxiety and find sustained interest in STEM fields (Lane et al., 2020; Groen et al, 2015; Tomasko et al., 2016). Lane et al. (2020) conducted a study of a six-week Comprehensive STEM Program (CSP, pseudonym), hosted by a majority White university in the Midwest. The goal was to acclimate students to academic and social life before their official start as freshmen, thus making student success more probable. The design of the course, deliberately set up in a mastery-learning approach, provided instances for students to: 1) work problems at the blackboard with the instructor in a non-threatening manner; 2) work in small groups; and 3) complete math assessments weekly to chart any progress. Students appreciated the informal nature of learning and the nonpunitive ethos evident in the class. Having such a safe space in the class, where errors could be made without causing academic penalty, helped students focus on learning STEM content rather than on earning a good grade (2015).

Capstone-Focused Research. Not only do effective SIPs tout hands-on instruction as a success factor, but they relatedly posit that learning experiences that culminate in capstone projects strengthen high school students' STEM interest (Momoh et al., 2014; Patel et al., 2021; Eeds et al., 2014; Huyer et al., 2018). Several SIPs maintain that having students engage in research opportunities and present their findings in poster or presentation form (i.e., capstones) foster meaningful connections between students and curriculum. The University of Alabama at Birmingham's Center for Community OutReach Development stresses such a component in its eight-week High School Summer Science III (SSI III) Program; student participants are required to investigate a manageable research question in molecular biology under the guidance of a faculty member and eventually present their findings at the university's Undergraduate Research Expo and local symposia (Patel et al., 2021).

Findings showed that these capstone experiences had a positive effect on students' STEM education and research career directions; an overwhelming majority of SSI III participants acknowledged increased confidence in presenting research and went on to complete STEM bachelor's degrees within five years of graduating (2021). As effective are projects presented to professors and government representatives (Momoh et al, 2014), submissions to national competitions and appropriate high school-level research journals (Eeds et al., 2014), and research posters (Huyer et al., 2018).

The Precollege for Engineering Systems (PCES) Program, a six-week summer initiative hosted by the engineering department at Howard University (HU), matched high school participants with faculty mentors and undergraduates or graduates to carry out major research projects (Momoh et al., 2014). Such projects were aimed at encouraging students to learn rigorous material under professional tutelage by training students to synthesize conceptual understanding associated with real-life problems. Requiring students to showcase their research to professors, high school teachers, and parents was a hallmark of the program's closing ceremony at the end of each summer. Throughout the program's existence, a whopping 90% of the students went on to major in electrical engineering and STEM-based fields; many have acquired STEM-based advanced degrees from top-tier universities to pursue engineering.

Cultivating Strategic Relationships with Program Professionals. Another notable feature of SIPs that is associated with students' STEM interest is the unique relationship students have with program professionals (Denson & Hill, 2010; Schumacher et al., 2009; Kendricks et al., 2019). Interaction with program professionals offers unique experiences that assist in students' perception of STEM. Involvement with professionals also provides students with an initial, real-life glimpse into the world of STEM before committing their lives to it. Specifically, working with competent faculty who double as mentors demystifies STEM and helps students understand that "normal" people exist in such academic spaces; additionally, apprenticeships give students an opportunity to tackle real research—often at real job sites as interns—while still in student mode.

Faculty Mentors. Faculty in SIPs often assume more than a teaching role; deliberate efforts are employed to have faculty shy away from the role of "teacher as god" toward students. In the mentioned PCES program at HU, not only did faculty members teach the students during the summer phase, but faculty also served as career advisors for students during the academic school year, especially with respect to challenges students may have had on research projects (Momoh, 2014). One student in the program keenly observed, "The PCES Summer Program … gave me a clear idea of [sic] about my future carrier [sic] goals. From the application process to [the closing] ceremony of the program, the mentors help us in every moment" (p. 1885). Although faculty-as-mentors are the main student relationship dynamic with regard to influencing student STEM interest in such programs, undergraduate student mentors and staff from students' ethnic background contribute to interest as well (Phelan et al., 2017; Grandy, 1998; Carpi et al., 2013).

Apprenticeships. In addition, students benefit from relationships with program professionals in the form of apprenticeships (Burgin et al., 2015; Salto et al., 2014). These prized experiences place students into internship opportunities with experienced faculty to develop and forge research projects. Burgin et al. (2015) analyzed a two-week STEM summer research program, in which eight high school rising juniors or seniors served as apprentices to established researchers in STEM fields. Qualitative findings revealed that the apprenticeship aspect of the program solidified or expanded students' interest in STEM, where many were encouraged to continue on with advanced courses.

Another program, the Apprenticeship Bridge to College (ABC) summer research program, is an eight-week, Southern California-based research internship program for underrepresented minority high school students. The program seeks students who desire to excel in biomedicine or to become physicians. Quantitative results found that the apprenticeship design of the program resonated strongly with participants; students developed confidence in their science ability, became motivated even more in their STEM pursuit, and benefited from sustained emotional support needed to pursue a science career (Salto et al., 2014).

Fostering Self-Efficacy. Students typically act on specific career interests to the extent that they feel that they can accomplish the tasks required for that particular career (Falco et al., 2019). Contributing to a heightened interest in STEM, especially among high schoolers who intend to pursue STEM in college, is their marked sense of belonging, dubbed self-efficacy. This noncognitive factor looms large in the lives of many students who seek to find their place in STEM spheres, making them feel less isolated on their journey. Often, this sense of self-efficacy in STEM is reinforced through one's gender- or community-based identity, like race, tribe, cultural group, and sexuality (Phelan et al., 2017; Bernstein et al., 2015; Xavier-Hall et al., 2022). A strong sense of belonging can further emanate from developing a strong connection with peers or near-peers who share a programmatic experiential bond and also from a connection that comes along with living on a college campus during the STEM experience (Nite et al., 2015; Knox et al., 2003; Lane et al., 2020).

Gender- and Community-Based Identity. The Broadening Access to Science Education (BASE) Camp, serving annual cohorts of roughly 25 high school girls at

Fairfield University, takes place in one of the richest counties in the U.S. A hands-on residential program, this Connecticut-based initiative is solely led by female STEM faculty or female STEM undergraduate majors (Phelan et al., 2017). The 25 student participants came from high schools in nearby Bridgeport, the most economically strapped city in Connecticut. Funded by the National Institute of Health through a five-year grant, the two-week program included a research component, a career exploration element, and a college counseling piece (2017). The pairing of faculty with participants in the Research Immersion Experience of the program proved especially meaningful to students. Pre- and post-camp survey data revealed a major increase in the girls' self-perceived confidence in STEM, which students felt was attributable to the all-female presence of program leadership (2017).

The Alaska Native Science and Engineering Program (ANSEP), a summer bridge program for high schoolers hosted by the University of Alaska Anchorage (UAA), seeks to prepare its students to pursue STEM majors in a learning community that embraces Alaska Native cultural identity. Combining a five-week residential summer experience and a four-week paid internship with strategic partners outside of the immediate Anchorage area, the program allows students to share in both the academic and hands-on aspects of the STEM journey. Many participants come from communities in Alaska that are largely rural and have never lived in a major city before (Bernstein et al., 2015). During the precollege experience, program administrators were deliberate about integrating social activities (e.g., Native dancing and hiking) amid rigorous coursework to fortify team building and foster a sense of community among students. In focus group sessions, participants "said that they appreciate the opportunity to interact with other high-achieving, STEM-oriented students from Native or rural communities" (p. 132), making the summer ordeal less isolating and promoting their sense of belonging to the college and, ultimately, to STEM.

Peer Support and On-Campus Acclimation. Peer support among participants and a degree of becoming used to the college are key factors in encouraging students' self-efficacy in STEM. Students who participated in the two-week Texas-T summer camp, hosted by a Research I university, lauded how the informal learning environment of the camp led to an increased sense of knowing; consequently, some of the summer students were instrumental in helping their peers understand many of the math concepts taught (Nite et al., 2015), reducing the competitive edge and fostering unity. In the Midwest's CSP, participants spoke highly of the peer-led recitation sessions; many were STEM upperclassmen and former participants in the same program (Lane et al., 2020). Interaction with these peers occurred in a one-on-one format or in groups. Findings heavily supported how important it was for participants to have had access to peer mentors as a measure of validation in the building of their STEM esteem, especially since these peers had recently taken the same class.

In addition, students' access to the college environment and its varied resources contribute to students' sense of belonging in their STEM journey (Nite et al., 2015; Johnson, 2016, Bernstein et al., 2015; Crawford et al., 2018). In the Texas-T camp, students' interacting with university members, residing in campus dorms, and eating in campus dining halls, helped students internalize belongingness not only to STEM but also the environment at which STEM would be taught (Nite et al., 2015). This tended to remove any sense of imposter syndrome among students, a common struggle for many as they attempt to find their affective place within STEM fields. Similarly, students, in a five-week residential summer SIP that focused on science and engineering preparation at a large mid-Atlantic university, lauded how living on campus was instrumental in helping them achieve a sense of association or kinship at the college (Johnson, 2016). Focus-group interviews found that this shared feeling of getting used to a college environment in a controlled, safe space with their peers was a notable aspect of the STEM summer experience and set the stage for eminent personal and STEM growth.

Moreover, Bernstein et al. (2015) corroborated similar findings in his study of the referenced Anchorage-based ANSEP. Living on the UAA campus for the summer proved to be eye opening for its heavily rural-based participants, as many of them hitherto had never been to a college campus before, let alone lived on one. One participant observed in one of ANSEP's evaluative focus-group sessions, "I live in a small village with only 800 people and we don't [sic] get much experience of college life and major road systems and it's [sic] helped me boost my confidence about what I want to do in the future" (p. 131). Hence, a certain degree of interaction between student and campus living is instrumental regarding developing and nurturing a sense of self-efficacy tied to students' STEM pursuit.

Exploring Factors Tangential to STEM Academic Pursuits. A notable portion of the success of SIPs for precollege students has very little to do with academics proper. Since many students who participate in these STEM programs are first-generation college attendees, they often require support in areas that are non-academic in nature but may significantly impact progress toward their STEM quest. Some research suggests that, when SIPs infuse these academically tangential support systems into programming, students tend to maintain STEM interest and persist with rigorous courses (Lane et al., 2020; Tomasko et al., 2016; Bernstein et al., 2015). Essentially, research echoes that SIPs tend to be more effective or beneficial when they “address the ‘whole student’ and not simply academic coursework” (Tomasko et al., 2016).

Time Management. In the study by Lane et al. (2020), summer bridge program administrators were deliberate in teaching the students lessons on time management in several ways. First, students’ schedules in CSP were designed in a way that mimicked how they would be during their first real semester (i.e., three times per week at shorter times or two times per week at longer times). This helped students “manage and prioritize time in order to prepare for their courses” (p. 169). They also structured the entire day’s worth of activities during the summer from early in the morning until late at night, driving home to students the importance of having an established routine to make their success more likely. Further, staff disseminated planners and time charts to students in an effort to help students get and remain organized, thus attempting to create positive habits that would spill over into their freshman year. Findings from interviews revealed “that principles and tools shared during advising sessions helped students better organize their time” (p. 170).

Community Service. Just referenced above, the same program provided students with a host of non-academic services intended to bolster their STEM interest. Under the umbrella of aiding students’ notion of time management, leaders specifically included community service as an outlet in which students would learn how to operationalize striking the balance between classes, social activities, and free time (Lane et al., 2020). In theory, this would hopefully assist students when they began their college life, having to keep up with a rigorous course set and maintaining a life outside of studies. Implications of the study showed that SIPs should incorporate predictable and structured time for students to study as well as take part in activities outside of academics to indeed enhance their academics.

Specialized Counseling. Some evidence shows that SIPs which incorporate varied support sessions for students are particularly valuable. The High School Intern Program at University of California San Francisco hosts one-on-one meetings with its Latino-dense student interns and counselors, who discuss the focus and grit needed for college; during the summer, interns and their families also attend a symposium on the college-applications process and financial aid (Witzel et al., 2020). This was notable especially since many of the parents had never attended college. In Fairfield University's BASE Camp, the largest increase in before-and-after-camp data was revealed in the category involving knowledge of the college admissions process (Phelan et al., 2017). Findings revealed that students and parents alike knew very little about admissions, financial aid, early action, and related non-academic matters before the camp; after the camp, however, students and parents knew considerably more, deeming it as "one of the most informative parts of the experience" (p. 69). In addition, the six-week Leadership 2.0 SIP, hosted by University of Cincinnati's College of Nursing, exposed its high school participants to counseling-rich symposia outside of the regular nursing course of study, including anxiety reduction, university orientation, transition to college, financial aid, and financial literacy workshops (Pritchard et al., 2016).

Interestingly, ANSEP, which prides itself in pushing STEM to its Native American high school clientele while celebrating the students' own cultural identities, provides guidance concerning expectations with regard to “appropriate dress” in a typical working milieu or field assignment (Bernstein et al., 2015). Literature is not clear about whether “appropriate dress” refers to an assimilation of a standard, Western-centric code of dress or if traditional Native garb is championed within the workplace or internship. The same program is deliberate about exposing students to other ideas related to professionalism like getting to work on time and interacting with colleagues and those in charge; the program especially “prioritizes building up participants’ verbal communication skills” (p. 130), key assets needed when students present about their internship experiences at the end of the summer. In Johns Hopkins School of Medicine, the Summer Academic Research Experience (SARE) Program hosted symposia on professionalism for its high school participants, in addition to science research. Principally, lessons center around writing a formal email, not texting or using a cell phone during conversations, removing headsets, giving firm handshakes, and resorting to high standards of ethics at and away from the job (Kabacoff et al., 2013).

Communication with Faculty Members. The coordinator in the Texas T-STEM center’s summer camp lauded the program’s facilitation in helping students develop “skills that enable them to communicate with faculty members and college students” (Nite et al., 2014, p. 1385). In the CSP, program administrators and staff used seminars and recitation sessions to stress to students the importance of strengthening relationships with faculty, showing up during office hours, and sitting in the front of the class (Lane et al., 2020). Student interviews corroborate how influential these components were to their perceived success in STEM. Relatedly, students attending office hours are able to receive tutorial assistance from faculty, shoring up any gaps that may exist in their STEM knowledge base (Tsui, 2007); if faculty tutorial help is limited because of practical time constraints, faculty can often refer students to tutorial services on campus, which are often free.

Although each SIP is unique in its own right, having its own set of particular aims and missions, each one seeks to do its part in shrinking the gap between the haves and have-nots in STEM spheres. In particular, the Upward Bound Math and Science program exists as one of those long-standing programs that has taken up the mantle of delivering STEM intervention to hundreds of thousands of high schoolers in America for over thirty years.

The Upward Bound Math and Science Program

To address what the U.S. sensed as long-standing gaps in science and mathematics with regard to race and a perceived loss of international competitive edge in STEM fields, the Department of Education (ED) created the Upward Bound Math and Science (UBMS) program in 1990 (Olsen et al., 2007). It was the sixth initiative of eight founded under the TRiO umbrella. The TRiO program—which has no literal acronymic interpretation—was simply named for the first three initiatives that were created from this legislative boon, one of which was the Upward Bound (UB) program. The UBMS program—one of the programs under the UB umbrella—was designed 25 years after the founding of UB, whose mission remains to make the dreams of college attendance and graduation a reality for FGLI students (McElroy & Armesto, 1998).

Once UB realized the great lack in STEM preparedness among its high school clientele, UBMS was created to address this specific need. Like UB, UBMS serves students nationwide through local implementation; unlike UB, UBMS focuses primarily on nurturing the science and math capabilities in students and steering them toward the pursuit of STEM majors in college and STEM-based careers. Whereas initially students were referred to UBMS from the UB talent pool, both programs now operate autonomously and have their own application process (Curtin & Cahalan, 2004). Students from target high schools apply for the program. A target area is defined as “a discrete local or regional geographical area designated by the applicant as the area to be served by an Upward Bound project”; a target school is “a school designated by the applicant as a focus of project services” (Upward Bound, 1995, p. 4750). Once admitted, students can begin the program after completing the eighth grade and remain until graduation from high school. However, students may apply and be accepted into the program through their eleventh-grade year. Figure 4 shows the current locations of UB and UBMS programs across the U.S. and U.S. territories.

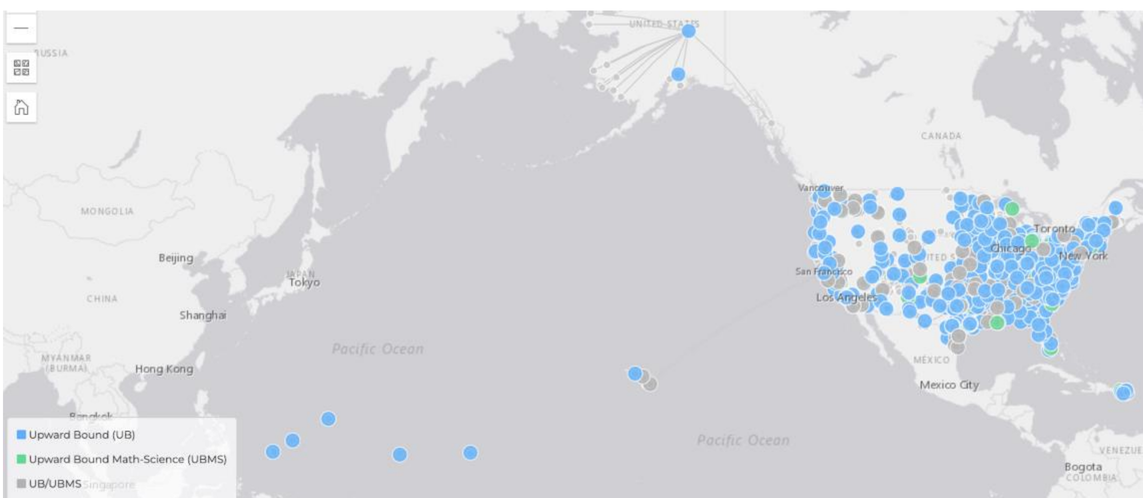


Figure 4. *Upward Bound and Upward Bound and Math Science Programs Across the U.S. and Its Territories*

Note: Image credit from https://bit.ly/3IIpXjR

Particularly, the UBMS program must abide by two federally mandated criteria from which to select students. Students must come from low-income families and those from which students' parents have no bachelor's degree. Two-thirds of the participants come from families who meet both of the mentioned criteria; the remainder is required to meet either one of the criteria (Curtin & Cahalan, 2004). A notable subset of this population reflects students with limited English proficiency. Support is yearlong, and the UBMS program must provide a summer instructional component lasting at least six weeks and a bridge program for participants during the summer between high school graduation and enrollment into college. Summer programs may be residential if university space and budget allow. Still going in full force, the UBMS program continues to provide continued support for a myriad of students across the country.

Universities and educational centers hosting UBMS programs expose students to direct practical experience in research laboratories, computer facilities, and other STEM-based, on-the-job training (Olsen et al., 2007). Further, students in the UBMS program shadow university faculty members who conduct science and mathematics research; in fact, under the guidance of faculty members or graduate school students, participants must coordinate and forge their own scientific research while in the program (Curtin & Cahalan, 2004). Currently, 211 UBMS programs that serve more than 13,100 high school students exist in the U.S. and Puerto Rico (Council for Opportunity in Education, 2023).

A Glance Back: The Effectiveness of UBMS

UBMS Under UB Covering. The UBMS program occupies a unique place in the existing literature. Having been a subsidiary under the UB umbrella for a long time, it has avoided much scrutiny from researchers related to its own autonomous efficacy. Its contribution of effectiveness or ineffectiveness has generally been shrouded within data analysis concerning the UB program as a whole. Having been around since 1965, UB has undergone a tremendous amount of inspection since its inception. The percentage of UB peer-reviewed articles pales in comparison to the ratio of analyses which find themselves as the subject of theses, published books, conference proceedings, reports, and an inordinate number of dissertations.

The few UB peer-reviewed studies tend to present findings on either extreme. Some researchers found that UB containing the aggregated UBMS data is tremendously effective in upping baccalaureate-degree numbers among FGLI students (e.g., Belz & Esten, 1998); others found that UB is depressingly ineffective, yielding no significant effect on students' high school credits earned or on whether students enrolled at any postsecondary institution (e.g., Myers et al., 2004). The Myers et al. study, conducted by Mathematica Policy Research (MPR), created quite the political stir, as Congress used the findings to reassess its willingness to continue investing in UB and federal programs like it. The George W. Bush administration initially proposed to defund UB based on such findings (Decker, 2014), but follow-up research cast doubt on study discoveries by pinpointing a number of statistical "violations," including a faulty sample design and conceptual formation of the treatment and control groups (Cahalan & Goodwin, 2014). Hence, funding continues.

UBMS Effectiveness Apart from UB. Having officially separated from the UB program proper in 1990, UBMS now had the opportunity to be scrutinized for its effectiveness based on its own merits. If peer-reviewed studies investigating UB were scant, those teasing out targeted UBMS data for analysis were scarcer still. Although some colleague-reviewed studies are sprinkled throughout the literature, most findings that focus strictly on UBMS—apart from any ties to UB—have been discovered through analyses and reports generated by independent researchers as they give account to ED or other entities having programmatic oversight.

In a longitudinal study of UBMS program participants from a regional sample spanning 26 high schools over five states (i.e., Southwest region) at the University of North Texas, two major findings emerged. These low-income UBMS students continued on to college when they finished high school at similar rates to students in the general population of all incomes in the same Southwest region (Pitre & Pitre, 2009). An apples-to-apples comparison also revealed that this same low-income sample group went on to attend college after graduation or attended at a later time "at rates higher than low-income U.S. students nationally" (p. 106). Whereas UBMS participants attended college at a rate of 82%, their comparable low-income counterparts nationwide attended at 44%.

Rahm et al. (2005) discussed the impacts of afterschool and community science programs for urban youth, many of whom became the first in their family to attend college. Researchers interviewed past participants in two programs, one of which was COSMOS, a creative renaming of the UBMS program. After collecting data from participants in the form of videos, field notes, interviews, and interviews, researchers highlighted a few observations from one of the male participants in the COSMOS program. Researchers offered no insight into why this particular student was chosen in the study. An immigrant from Mexico and a science major at the time of the interview, the participant lauded how the "mentorship experience in the biochemistry lab further strengthened [his] interest (in his STEM pursuit)" (p. 288). Hence, his immersion into the program's structure helped him see the value of having mentors to guide him through frustrations tied to the slow-going nature of authentic research projects; his persistence assisted in making his research experience meaningful. Though only an anecdotal incidence, it shed light on the impact of the program through a more micro-focused perspective; thus, one hesitates to generalize from these researchers' efforts.

Seftor and Calcago (2010) provided an impact analysis of UBMS on a national level, in which they report on the program's impact for low-income students seven to nine years after high school graduation. Results suggest the program's positive, significant impact on students' college attendance at a four-year institution (i.e., more selective institutions) and a negative impact on attendance at an institution other than a two- or four-year institution. Using a matched comparison sample from the regular reported UB group, researchers found that UBMS "increased the likelihood of majoring or intending to major in math or science from 25.8 percent to 31.6 percent overall and from 20.2 percent to 24.7 percent at four-year colleges and universities, although neither of these impacts is statistically different from zero at conventional levels" (pp. 39–40).

In a different study, researchers at Research Triangle Institute (RTI) explored national data for the UBMS participants who finished high school during the 2004–05 academic term; since the study included data through 2005–06, researchers were able to interpret findings through a longitudinal lens and provide insight concerning postsecondary transitions for the cohort (Knapp et al., 2008). Three dominant findings surfaced.

As one of the major aims of the program is to push students to attend college, findings first revealed that, out of the 2,936 UBMS students, 86.1% of them enrolled in a postsecondary institution; such data was verified by transcripts, institution codes, and if financial aid was awarded (2008). Second, results highlighted the association between the duration of students' participation in the program and their pursuit of postsecondary education. Students who participated in the UBMS program longer were more likely to continue on to postsecondary education than those who participated in the program for a shorter period of time; whereas 80% of UBMS students who participated in the program for less than a year enrolled in a postsecondary institution, 94.3% of them who participated for three years or more enrolled in the same (2008). This suggests that longer affiliation with the UBMS program likely increased the probability of college enrollment.

Finally, at all comparable levels of time affiliated with UBMS, females were more likely to pursue postsecondary education at a higher rate than their male counterparts; for example, whereas 82.9% of female students who participated in the program for less than a year enrolled in a postsecondary institution, 75.6% of male students who participated in the program for the same length of time enrolled in the same (2008). Not dissimilar from a more steady and relatively recent trend, RTI findings bear out much of the same in extant literature: females are pursuing postsecondary education at a rate higher than males (Aud et al., 2011; Robson et al., 2018; García-Holgado et al., 2020).

Limitations in Existing UBMS Studies

Similar to those of its UB counterpart, findings on and insight about the effectiveness of the UBMS program are largely situated in various book chapters (e.g., Williams et al., 2022), independent reports (e.g., Olsen et al., 2007), conference proceedings (e.g., Markley & Fail, 2005), and dissertations (e.g., Jogie-Cregger, 2017). Though they offer a unique perspective on UBMS and its supposed impact, they are not subject to the much-valued peer-review process. Sidestepping this critical, intellectual checkpoint suggests that major issues in the research process could have been overlooked or possibly flawed.

In the study by Olsen et al. (2007), research efforts focused solely on UBMS and its effectiveness for students participating during the summers of 1993, 1994, and 1995. Researchers conducted impact analyses, highlighting several findings. The study suggested that the UBMS program increased the probability of bettering students' grades in high school; enrolling in chemistry and physics in high school, not math; attending more selective universities; and obtaining a postsecondary STEM degree. Although the study attempted to draw inferences concerning this latter finding, no reasoning or data analysis was provided to substantiate said claim. Asserting that the program significantly impacted students four to six years removed from its influence ignores key factors contributing to postsecondary STEM degree attainment or non-attainment during college years. The task of assessing an individual program's influence becomes more difficult when mixed with other, unacknowledged variables that appear later in the evaluative equation.

The study also admitted that possible selection bias linked to gauging students' interest in pursuing STEM careers may have been the biggest weakness in the study. When deciding what kind of effect the program had on former students' pursuit of STEM careers, the selection of those who participated in the survey was not random. Former participants who entered fields other than STEM may not have been aggressively sought after to offer their perspective on the program; such a reality made for a potentially less expansive view of the program's impact than would be obtained if selection bias were not present.

Markley and Fail (2005), in their proceedings, highlighted the UBMS program at The Pennsylvania State University (Penn State) for a group of summer students. In partnership with the Earth and Mineral Science (EMS) Program, students worked through regular curriculum in the UBMS program and an additional 30 hours of directed research with program faculty. Findings support how beneficial relationships were between participants, faculty, mentors and graduate students, opening pathways for students to take part in research experiences and fostering a strong sense of community.

Proceedings stated that summer participants were exposed to a number of pre- and post-program questionnaires as well as pre- and post-program math readiness surveys. Such data are indeed vital in determining what quantifiable impacts the UBMS-EMS partnership had or did not have on students. The anxious reader is left wanting, however, as results of both measurement instruments remain a mystery. One may imagine that the UBMS program and the research component addendum to the summer curriculum impacted participants in a significantly positive manner. Sharing specific qualitative results in the proceedings would tend to have corroborated what the researchers unequivocally defend: that all involved parties—faculty, participants, and Penn State alike—benefited greatly from student participation in the UBMS-EMS program partnership. It is duly noted in the proceedings that the pre- and post-program questionnaires were available at the 2005 Women in Engineering ProActive Network/National Association of Multicultural Program Advocates Joint Conference.

Knapp et al. (2008) in their RIT-led study made predictive inferences by relying on percentage comparisons across various variables of interest. For example, as alluded to earlier, the percentage of students who stayed enrolled in the program longer than others compared against same-level graduation percentages signaled the predictive power of duration of affiliation onto program effectiveness. Making inferences solely on the comparison of basic percentages, however, tends to minimize possible interaction of factors (i.e., mediation and moderation) onto results. This is especially the case when attempting to make conjectures related to program effects and impact analyses. More advanced statistical techniques are often appropriate when mostly quantitative data are at researchers' disposal. The study herein seeks to capitalize on this methodological and statistical shortcoming, offering some attempt at understanding program evaluation from this vantage point.

Summarily, however, a more conceptual limitation exists with respect to UBMS findings in general. Specifics concerning methodology and prediction protocol within UBMS studies aside, a much broader issue regarding the evaluation of the program lingers. On a larger scale, the rate at which the ED allows for independent evaluations of the UBMS program raises a brow. The most recent national UBMS independent evaluations have been published by Olsen et al. (2007), Seftor and Calcagno (2010), and Heuer et al. (2016). Some maintain that this trend of evaluation of the program is disheartening in that it fails to inform the ED of the program's challenges and successes in what some might deem a timely fashion. Though no time frame for regular program evaluation is set in stone, some researchers assert that programs should be evaluated every three to five years to gauge their impact (Fitch, 2023). With annual federal budget allocations hovering at approximately $65 million per year for the program (U.S. Department of Education, 2022), frequent and extensive evaluation of the program would inform Congress of its effectiveness and whether the program is worth the continued investment in taxpayers' resources.

Confirmatory Program Evaluation: A Methodological Framework

Before settling in on the purpose of the study and research questions to be explored, one considers the structure by which the study itself is guided. Such a framework sets the analytical stage needed herein to conduct a sensible evaluation of the UBMS program. Indeed, evaluation of programs occupies a unique space in the world of a program's existence. Findings from some program evaluations hold tremendous import because of their role in determining if programs persist or reach their bitter end. There is no shortage of instances where appraisals of programs often reveal affiliation bias, in which the evaluator is a part of the program staff, leadership, or the principal investigator himself (e.g., Momoh et al., 2014).

Relatedly, when programs are supported by local, regional, or federal dollars, another layer of evaluative pressure sometimes arises to "prove" how said programs are effective regarding their stated objectives even if, in reality, they are not. Having a direct connection with a program and leading the efforts to evaluate it need not necessarily sacrifice validity or suggest bias. Such an affiliation just needs to be fully disclosed. More importantly, findings from program evaluation become highly defendable when methods utilized are theory driven (Pope et al., 2019); when evaluations are conducted by non-stakeholders and those uninfluenced by stakeholders (Giancola, 2020); and when data analysis practices are inflexible and made available to duly vetted inquiring minds (Gorman, 2018).

Several theory-driven methods for evaluating programs exist, all having their own sense of utility and mission. One such method gaining momentum over the last quarter century is confirmatory program evaluation (CPE), developed by Reynolds. Its purpose is unwavering.

> Confirmatory program evaluation is one method of conducting a theory-driven evaluation in which the objective is to facilitate causal inference about the relationship between program participation and measured outcomes. It is an outcome or impact evaluation in which hypotheses about the program are tested, based on the program theory. Unlike theory-driven evaluation generally, CPE specifically focuses on outcomes by quantitatively estimating program impact. CPE is primarily designed for investigating effects at the postprogram stage and during postprogram follow-up periods. In many respects, CPE can be viewed as a longitudinal process evaluation. (Reynolds, 1998, p. 207)

Drawing upon notions about causal inferences, which have permeated the literature since the 1960s (Freedman, 1967; Rossi & Wright, 1977; Briggs, 2004), CPE aims to analyze the impact of program intervention on outcomes. Often used in tandem with correlation-based statistical techniques (e.g., path analysis, multivariate regression), the theory-driven method establishes and assesses an a priori model in light of a program's alleged impact on outcomes (Reynolds, 2005).

Tendencies Toward Causality

Essentially, according to CPE theory, a tenable program effect can likely be captured by undertaking a systemic evaluation of various facets of a program-outcome association. Unlike the more traditional randomized control trial, CPE specializes in handling designs that are nonexperimental or for which it is not possible or plausible to obtain a control-based comparison group (Reynolds, 1998). Further, unlike Bandura's

Social Cognitive Career Theory approach, CPE does not particularly seek to test for self-efficacy or for any perceived barriers that could play a role in career choice (i.e., the outcome), unless a program is deliberate about including such in its goal statements and collecting relevant data (Lent & Brown, 1996). The theory-driven evaluative methodology is situated in emergent literature across various disciplines, including psychology (Kratochwill & Stoiber, 2002), the social sciences (Smith & Teasley, 2009), health care (McGilton et al., 2005), and education (Reynolds, 2005; Gravois & Rosenfield, 2002; Hense et al., 2009). Its ultimate mission is to unravel mysteries with respect to possible causal connections between variables.

In CPE, causality becomes more likely to exist through investigating several criteria associated with program intervention and whether it achieves its outcomes (Reynolds, 1998). A sample of these criteria follows:

1. No outcomes are considered until participation in the program is complete or ends before expected.
2. The more participants engage with the program, in all of its many services and over the maximum amount of time, the more likely that outcomes experienced are because of the association.
3. Generally, as the amount of time and duration of program participation increases (e.g., years of affiliation, daily contact hours, number of days per week), the more likely that outcomes experienced are because of the association. This is referred to as the dosage-response relationship.

4. If the associations between the program intervention and outcomes found in this study hold consistently when conditioned on subsamples, causal inference is more likely.

Limitations and Challenges

The largest challenge facing CPE is a program's lack of program theory or the failure to diligently implement one that may exist. When a program is unable to convey or articulate its objective mission, CPE has a weak evaluative leg on which to stand (1998). Logical variables are to be explored, which emanate ideally from existing literature and a program's stated mission; otherwise, difficulty lies in establishing possible causal relations to outcomes. Further, shoddy implementation of objectives that do exist as well as lazy data collection hamstring CPE and its ability to arrive at valid findings. For example, a program may advertise that its internship component contributes significantly to students' career interests. If program staff exerts little to no effort in helping students obtain internships or keeps inaccurate data concerning viable internship experiences, this component should not be considered in CPE; possible causality becomes difficult to measure.

Last, CPE relies on linearly based models like path analysis in its design (Jeon, 2015). In real life, variables do not always meet this particular criterion in a study. Overcoming challenges of the sort, however, are not insurmountable. Legal statistical transformation of the data (e.g., log transformations) or other inventive techniques of analysis (e.g., bootstrapping) generally solves such dilemmas. It becomes the responsibility of the researcher to consider assumptions around linearly based models and make the adjustments as necessary in the analysis. Nonetheless, path analytic modeling remains an ever-present, well-grounded tool for examining causal inferences in vibrant fields like STEM (Sellami et al., 2017; Botnaru et al., 2021;), thus making CPE a viable avenue for exploration.

Purpose of the Study and Research Questions

Evaluations of SIPs like UBMS have become as plenteous as SIPs themselves. Assessing whether these programs are "working" becomes the order of the academic day for many. Whether or not SIPs achieve the outcomes that they claim has tremendous impact, as a huge percentage of them are supported by dollars at the federal and state levels. While many of these program evaluations have concluded that certain SIPs are making marked positive impacts in the STEM trajectory of students' lives, others have rendered other programs as virtually ineffective and failing at their mission (Boeve-de Paux et al., 2020; Alvarado & Muniz, 2018).

The Purpose

One goal of this dissertation is to evaluate the effectiveness of Temple University's UBMS program in light of its own stated objectives. Second, the study focuses on how UBMS contrasts with UB on the campus. Since UBMS is an offshoot of UB, with a specific mission of focusing on STEM preparation, one becomes curious to investigate how both programs stack up concerning particular program outcomes, especially with respect to objectives that supposedly and uniquely define the two programs in theory. This dissertation mainly contributes to the literature by analyzing the efficacy of the program through a CPE-based lens. Hence, third and primarily, the study entertains path analytic methods within the CPE framework, considering two key outcomes related to UBMS's aim. The dissertation then explores findings from the perspective of causal inference, as informed by CPE theory. No other study, at present, has evaluated this program from this theoretical and statistical vantage point.

Research Questions

The overarching research questions of this study are:

I) How do UBMS students perform in light of the program's own projected goals, as outlined in the proposal documentation?

II) How do students in the UBMS program compare with those in the UB program regarding: 1) advanced math course completion, 2) high school state proficient achievement level in mathematics, and 3) postsecondary enrollment?

III) How does the UBMS model in the study fare against scrutiny by the Confirmatory Program Evaluation (CPE) method of assessment? That is,

a) To what degree did students' entering grade level, apprenticeship involvement, employment, participation in community service, scope of program participation, and time of affiliation with the program predict whether they obtained a rigorous course of study by the twelfth grade?

b) To what degree do the same variables predict whether they completed advanced mathematics courses beyond algebra 1 by the twelfth grade?

c) What do results suggest about the plausibility of causal inference and also about the effectiveness of the UBMS program?

An examination of the UBMS program with a focus on these research questions can provide some awareness concerning program efficacy within the confines of its own program theory. The questions allow for the probing of measured variables associated with the program and their potential impact on what makes the program effective or not. On a more concrete and less academic level, this exploration may do well to generally inform decisions between secondary and postsecondary leadership as both seek to adequately serve the needs of FGLI students who wish to excel in STEM. The academic handoff of students from high school to college is a sensitive one, requiring both parties to make strategic decisions to make the transition in STEM as smoothly as possible for all students. Proper evaluation of university-run programs like UBMS, which reach back to assist students in their surrounding community, can be crucial to fostering healthy partnerships between secondary and postsecondary stakeholders as they strive to make a difference in the lives of these students.

CHAPTER 3

METHODOLOGY

In this chapter, the basic context surrounding the data is discussed. Before any discussion of methodology proper, one becomes acquainted with the complexion of the UBMS program at Temple University, of a few of the target schools associated with the program, and of the UBMS students themselves. Focus then shifts to the defining of data measures and variables of interest in order to explore the various hypotheses in the study.

Administrative Changes: UBMS Oversight at Temple

Before considering the data for the study, one considers the administrative environment of the program in which the data was collected. As with any service program on a campus setting, visioning and implementation are often directly related to program leadership. The UBMS program at Temple from 2008–2021 is no different. Though housed and run within the borders of one campus, a few administrative shifts in the program's leadership are to be noted. Administrative quirks and idiosyncrasies may often influence the overall environment in which data are collected, guidelines affecting how and what data are collected, and program follow-up. With respect to the UBMS program at Temple, three major administrative changes inform the realities undergirding the data during this 13-year period. One observes these programmatic shifts during Fall 2008 – Summer 2015, Summer 2015 – Fall 2017, and Fall 2017 – Summer 2022.

Administrative Period One: From Fall 2008 – Summer 2015

During this period, the UBMS program was shepherded and administered within the Russell Conwell Learning Center on the campus. It was a part of the Vice Provost for

Undergraduate Studies' portfolio. The program was under the directorship of the Center, whose focus was not solely on the UBMS program entirely. All programs under its leadership, including UBMS, received the attention and guidance provided by staff in the Center. Toward the end of this time, this Center at Temple was disbanded. At the time of the disbanding, the UBMS program was in the middle of its 2012–2017 grant cycle. As such, it was vital that the program remain viable so that students would continue to receive uninterrupted academic and counseling services.

Administrative Period Two: From Summer 2015 – Fall 2017

After the Learning Center closed, the UBMS program became administered by the CEHD, which was referred to at the time as the College of Education. CEHD adopted the UBMS program from the Vice Provost's portfolio. Staff of the program became CEHD employees. Students received services during this period as program directors changed twice. The director that transitioned from the Learning Center lasted one year, and an interim director was assigned to oversee the program during the final year of the grant cycle.

As the cycle neared its end and the opportunity for a new cycle became eminent, directorship explored opportunities to have the UBMS program collaborate and partner with Steppingstone Scholars, a program whose mission is "to create access to educational and career opportunities for talented, underserved Philadelphia students, combating systemic racial and socioeconomic inequality" (Frasca, 2022). The College submitted an application for a new five-year award with Steppingstone as a sub-contractor on the project.

Administrative Period Three: From Fall 2017 – Summer 2022

The UBMS program, in partnership with Steppingstone Scholars, started in September of 2017. UBMS directorship and staff were employees of Steppingstone Scholars. Supervision of the program would come from the relevant assistant dean at Temple, whose focus was on programs related to college access and persistence. UBMS students received summer and academic-year services with the most substantial change in program design and delivery under the new grant being that residential summer experiences on Temple's Main Campus could no longer be afforded. However, COVID-19 forced UBMS services to be offered only through virtual means from 2020 to 2021. In-person services would gradually resume in 2022.

Behind the Data Scene

Before delving into an analysis of the data, it becomes beneficial to visualize the backdrop against which the data exist. No significant revelations arise from such a visualization, as the length of time that the program is under particular leadership is not long. One assumes that any programmatic effects under any given leadership would take a fair amount of time to be observed. Certainly, switching to another leadership team to lead the program for two years is not ideal but would not terribly alter student results, one might argue. However, it may render some information as having more variability that would otherwise be deemed more uniform or less volatile if under the auspices of only one leadership team.

Hence, considering the phenomenon as leadership turnover in this instance, as seen in Figure 5, may only contribute to the discussion of the given variability within a certain variable as it relates to the study. For example, when it comes to the analysis with the variable of students' duration of time in the program, one administration may choose program ending dates differently for UBMS students in its supervision than would another administration. Therein lies a way in which data in this column, although an objective measure, pays the price for programmatic shifting in administration. Thus, understanding this specific data requires a basic nod acknowledging the intersection between the grant cycles and the stated administrative changes; nonetheless, none of these changes are assumed to play a major role in analyzing the efficacy of the program since the window of time between administrative changes is too short and the time needed in order to witness possible effects in student results is too long.

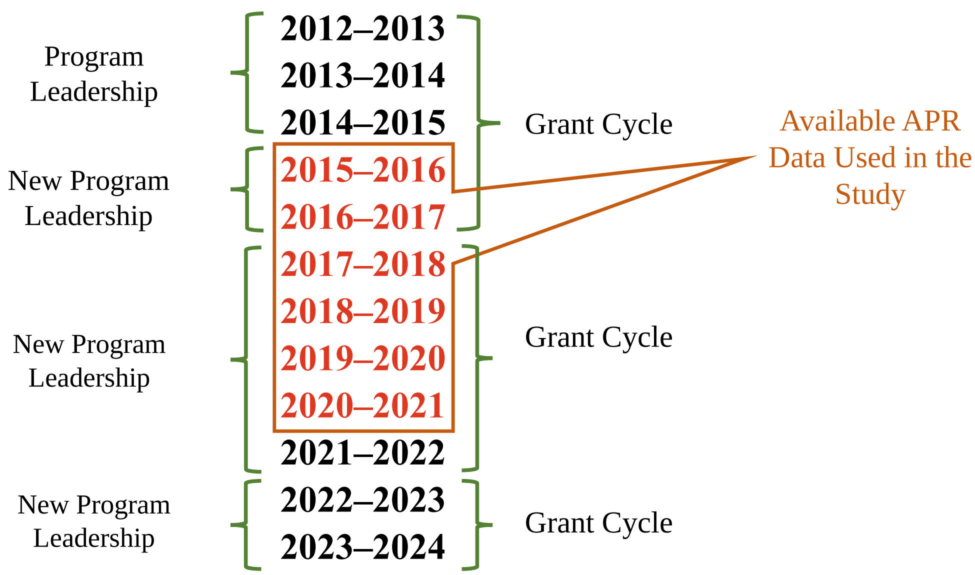


Figure 5. *Temple's Upward Bound Math and Science Program Administrative and Grant Cycles, 2012–2024*

The Data

The study herein considers data from UBMS Annual Performance Reports (APRs) provided by Temple University's College of Education and Human Development

(CEHD). All data come from Section II of the APRs and provides information for students who participated in the UBMS program and graduated from high school between 2008–2021. Specifically, 67 data points are available for most participants. The ED requires all UBMS program host institutions and educational centers to collect, store, and report such data each year in EXCEL or comma-separated values (CSV) format. All column names in submitted files must match the "Database column names" requested by the ED. Grantees must further follow instructions in the "Valid field content" column, which helps to guide the scoring of responses. Following these instructions ensures that the data preserves a sense of uniformity and strengthens reliability and validity in the analysis of the data. As indicated to the Institutional Review Board (IRB), all data was de-identified prior to data inspection and analysis. Before discussing measures related to the broader investigation and research questions, one becomes acquainted with this specific set of data and how it is situated within the Temple University community during the period of study.

Target Schools and Target Areas

Before discussing Temple's UBMS students in the study, one should consider schools from which these students come. A glance at the schools familiarizes one with program realities in conjunction with students' formal secondary educational settings. The program conceivably receives students from target and non-target schools, all of which are located within the target area. Whereas a target area refers to a specific local or regional geographical area designated by prospective funding grantees as the area to be serviced by the UBMS program, a target school refers to a school within a target area that is the focus of special UBMS attention and/or services (Upward Bound Program, 1995a).

Non-target schools are schools within the target area that receive services from the program but not to the concentrated degree target schools do. Target schools become official partners with the campus and thus receive special benefits that accompany the unique partnership. Examples of these benefits can include having special programming on site at the target school and offering high school credit for courses taken during the UBMS summer component.

For Temple, the target area is the entire city of Philadelphia, which includes public district and charter schools. Students attending parochial or private schools are ineligible for participation. Further, those who reside outside of the city of Philadelphia are ineligible. Table 1 reveals the number of target schools and non-target schools from which UBMS students at Temple are enrolled over the period of study. Data reflect the number of target or non-target schools during the particular grant cycle of interest.

Table 1

Temple's Upward Bound Math and Science Program's Target and non-Target Schools by Grant Cycle

UBMS Grant Cycle	Number of Target Schools	Number of non-Target Schools	Total
2012–2017	4 (8.2%)	45 (91.8%)	49 (100%)
2017–2022	6 (30%)	14 (70%)	20 (100%)

One target school appears in both grant cycles; hence, data show that there are a total of nine distinct target schools. Of course, all of these target schools fall within the target area of the city of Philadelphia. Focusing on these specific school types affords program leadership the opportunity to gauge students’ progress along the STEM journey in comparison to their non-target peers. An analysis of students in these schools would theoretically offer some insight on how the UBMS program somehow levels the STEM playing ground for them. Figure 6 shows these nine target schools, illustrating a rough estimate of distance from Temple's main campus.

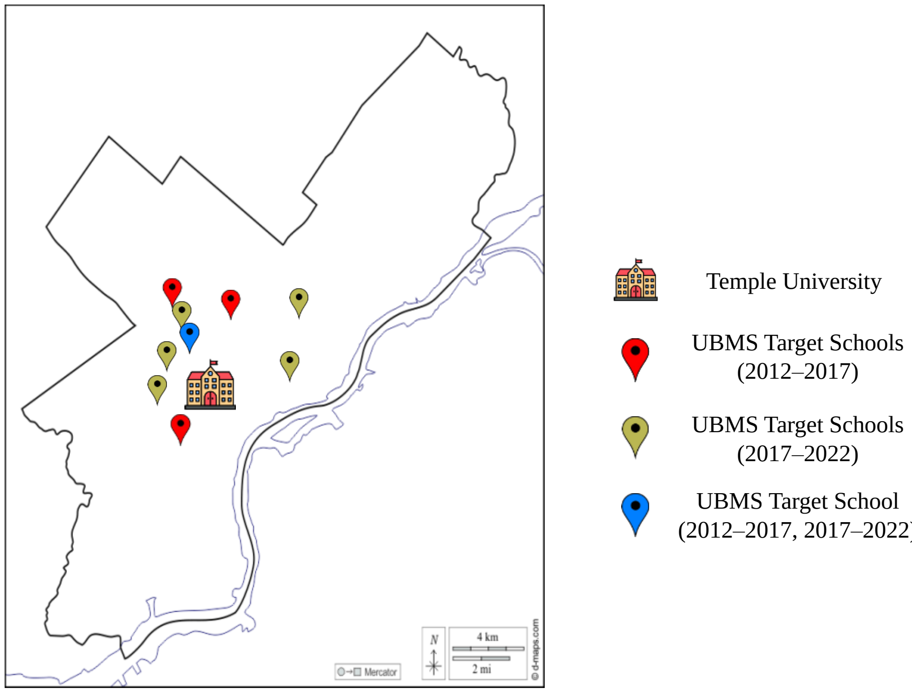


Figure 6. *Temple's Upward Bound Math and Science Target Schools, 2012–2022*

Note: Map credit from https://bit.ly/3t0NLKT. University image credit courtesy of Freepik. Pin image credit courtesy of Clkr.

And Table 2 provides relevant details about these target schools located in the Philadelphia area. Data are provided concerning the following as related to target schools of interest: gender breakdown, student-to-teacher ratio, race/ethnicity, and students' eligibility regarding free lunch. These target schools possess several distinguishing characteristics. One of the target schools in Figure 6 is omitted in Table 2 since it has been closed for nearly a decade. Another school (School 7) was a target school during both grant cycles

Table 2

Characteristics of Temple's Upward Bound Math and Science Program Target Schools, 2012–2024

High School	Gender		Number of Students to 1 Teacher	Race/Ethnicity				Free Lunch Eligible
	Male	Female		Black	Hispanic	White	Asian	
School 1	278 (59.7%)	188 (40.3%)	11.0	328 (70.4%)	93 (20.0%)	10 (2.1%)	16 (3.4%)	100.0%
School 2	403 (45.0%)	493 (55.0%)	17.5	800 (89.3%)	62 (6.9%)	6 (.7%)	3 (.3%)	99.9%
School 3	566 (61.3%)	357 (38.7%)	13.0	402 (43.6%)	428 (46.4%)	46 (5.0%)	5 (.5%)	99.9%
School 4	317 (55.5%)	254 (44.5%)	13.3	252 (44.1%)	256 (44.8%)	26 (4.6%)	9 (1.6%)	100.0%
School 5	261 (66.6%)	131 (33.4%)	12.6	323 (82.4%)	39 (9.9%)	10 (2.6%)	1 (.3%)	100.0%
School 6	110 (54.2%)	93 (45.8%)	10.0	190 (93.6%)	8 (3.9%)	1 (0.5%)	0 (0%)	100.0%
School 7	695 (58.1%)	501 (41.9%)	51.55	412 (34.4%)	661 (55.3%)	13 (1.1%)	67 (5.6%)	99.7%

of 2012–2017 and 2017–2022. In only one case (School 2), the number of females exceeds that of males. Student-to-teacher ratios range from 10 to a whopping 51.55. For most of the schools, the majority of students are Black. In other instances, most of the students are Hispanic (Schools 3, 6, 7). Virtually all students in the target schools are eligible for free lunch. Not shown in Table 2, the closest target school to Temple is only one mile away, while the farthest is 6.3 miles away.

UBMS Students: A Closer Look

Prospective students undergo a uniform application process and are accepted on a rolling basis; they may apply online or by downloading a paper application and mailing. Supporting documents—official transcripts, parents' tax returns, recommendation letters, and the like—are required immediately after the initial application submission. Students attend in-person or virtual interviews with program staff if they meet eligibility requirements and are expected to start actively participating in the program immediately after they and their parents complete a mandatory orientation session.

Generally, students in the ninth, tenth, or eleventh grade are eligible for participation in the UBMS program. Over the 13-year period, a total of 374 students received some type of service from the program. Some remained with the program until graduation, while others severed ties with the program for a number of reasons, including pursuing employment, relocating outside of the target area, and no longer being interested in the program itself. Figure 7 provides a closer look at the 374 UBMS students who comprise the overall pool of students in the program for the study.

Not particularly surprising, given the program's location in the heart of Philadelphia, a city with a population that is approximately 43% Black, almost three-quarters of the program participants are Black. The number of females almost doubles that of males. About 70% of the participants were identified as low-income and first-generation students upon their entry into the program; in the chart on program eligibility,

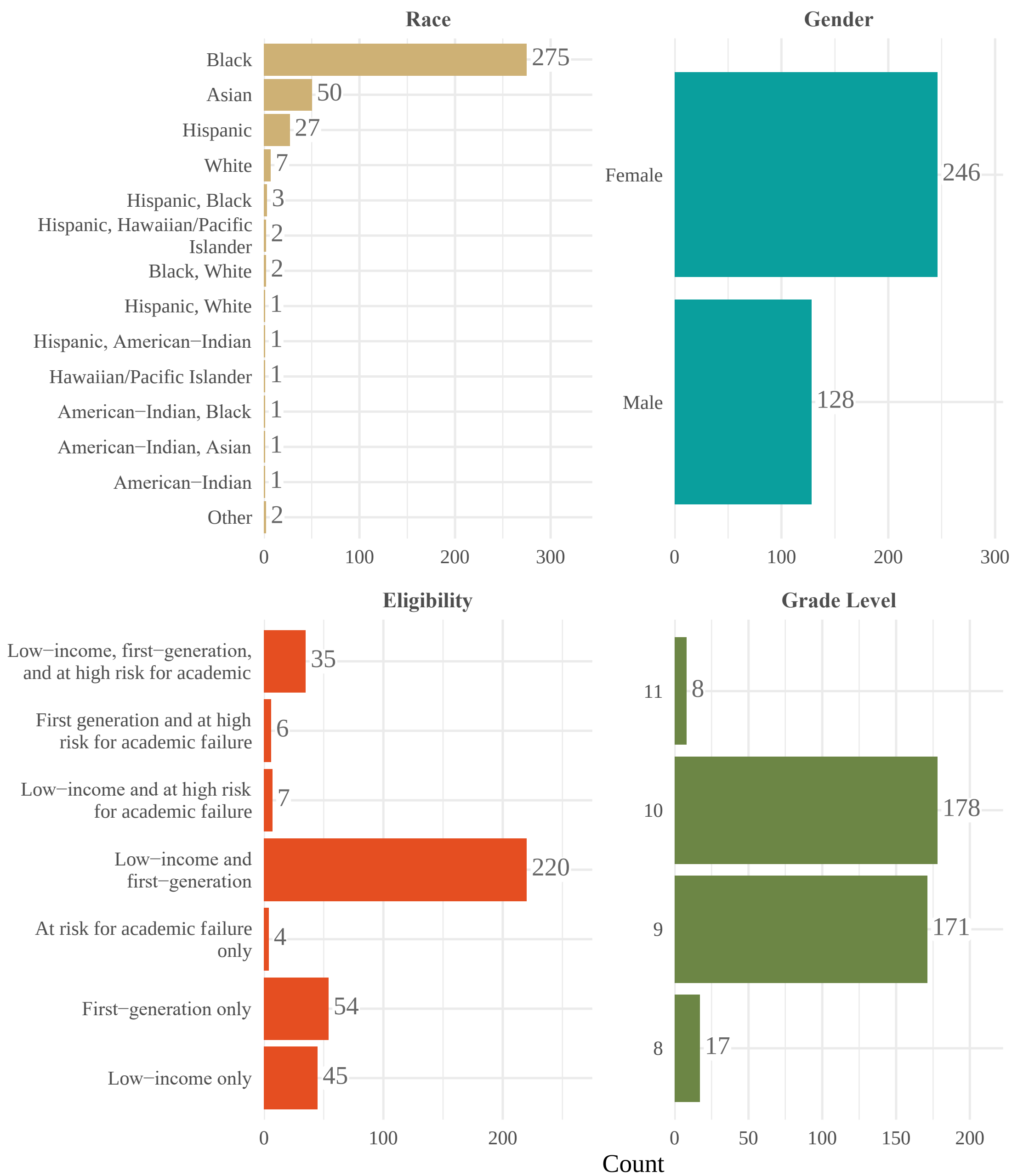


Figure 7. *Temple's Upward Bound Math and Science Students at a Glance, 2008–2021*

these students were classified as low-income and first-generation (220) or low-income, first-generation, and at high risk (35). This slightly exceeds the program requirement, which specifies that two-thirds of program participants must meet this threshold. Of these students, most of them entered the program as rising tenth graders, while the fewest number entered as rising eleventh graders.

Measures

Out of the many variables included in the data, several key ones become the measures of focus across the four research questions. Those considered herein are supported by their presence in the extant literature in light of the stated goals expressed by the program theory. The UBMS mission is to strengthen students' math and science skills and to encourage participants to pursue postsecondary STEM education. In the context of the UBMS program, several logical variables are conceivably linked to the two program outcomes. The 2020–21 UBMS Annual Performance Report (APR) provides descriptions of the selected variables in its Record Structure for Participant List (Section II); other definitions are located in the Supplemental Instructions for Specific Fields in the program's general instructions for the APR.

1. *Grade level at the beginning of the program*

   This variable discloses participants' grade level when they began the UBMS program.

2. *Performance on state assessments*

   This variable indicates whether students achieved the level of proficiency on state assessments in reading/language arts and math.

3. *Work study*

   Technically, this variable (as referred to in the Higher Education Act of 1965) focuses on whether students participated in internships and/or employment arranged for by the program. Its purpose is to expose students to careers that require a degree beyond high school.

4. *Community service*

   This variable assesses whether students participated in any UBMS-facilitated activity or activities designed to serve a community. Community service does not have to be integrated into a student's academic work in UBMS or at his or her school.

5. *Employment*

   Employment refers to jobs of at least 10 hours per week arranged either by the project or by the participants themselves that are separate from the program. These jobs are primarily to allow students to earn some income while in school and participating in the program.

6. *Program participation level*

   This variable conveys participants' degree of involvement with the UBMS program.

7. *Length of time affiliated with the program*

   This variable conveys how long participants have been affiliated with the UBMS program. It is the difference in days between the date the students first received service from the UBMS program and the date of last service. If students participated in the summer bridge component, this date could extend beyond high school graduation.

8. *Retention and high school graduation*

   In the data, one is able to determine if students graduated from high school or if they stopped short of earning their diploma.

9. *Rigorous course of study*

   This variable assesses whether participants obtained a rigorous course of study by the end of the twelfth grade. A rigorous course of study, as defined by federal regulations (Upward Bound, 1995b), refers to a program of study that is:

   (1) Established by a state educational agency (SEA) or local educational agency (LEA) and recognized as a rigorous secondary school program of study by the Secretary through the process described in 34 C.F.R. 691.16(a) through (c) for the Academic Competitiveness Grant (ACG) Program;

   (2) An advanced or honors secondary school program established by States;

   (3) Any secondary school program in which a student successfully completes at a minimum the following courses:

   (i) Four years of English.

   (ii) Three years of mathematics, including algebra I and a higher-level class such as algebra II, geometry, or data analysis and statistics.

   (iii) Three years of science, including one year each of at least two of the following courses: biology, chemistry, and physics.

   (iv) Three years of social studies.

(v) One year of a language other than English;

(4) A secondary school program identified by a State-level partnership that is recognized by the State Scholars Initiative of the Western Interstate Commission for Higher Education (WICHE), Boulder, Colorado;

(5) Any secondary school program for a student who completes at least two courses from an International Baccalaureate Diploma Program sponsored by the International Baccalaureate Organization, Geneva, Switzerland, and receives a score of a "4" or higher on the examinations for at least two of those courses; or

(6) Any secondary school program for a student who completes at least two Advanced Placement courses and receives a score of "3" or higher on the College Board's Advanced Placement Program Exams for at least two of those courses.

10. *Advanced math courses completed*

This variable assesses whether participants completed two years of mathematics beyond algebra 1 (e.g., geometry, algebra 2, trigonometry, pre-calculus, or calculus) by the end of the twelfth grade.

11. *High school grade point average (GPA)*

This variable summarizes students' academic performance on a 4.0 scale. Information is available on a weighted and unweighted basis.

12. *Postsecondary enrollment*

This variable discloses if (and at what level) students enrolled in college immediately following their high school graduation. Students may have received notification of acceptance but deferred one semester, enrolling in the following spring (mostly pandemic related).

Unlike an average set of data, the data for this study furnishes varying amounts of information, depending on the variable being explored. Program leaders are required to collect and store data concerning various variables for varying lengths of time. Hence, all students will not be used for all sub-analyses in the study. For example, GPAs are only reported for the year of the current APR. The analyst only has APRs for 2015–2016 through 2020–2021. So, no GPAs are available for students before 2016, although they are still present in the overall data pool. At the same time, data-collection procedures for students' proficiency level on state assessments allow for information storage for a longer period of time; hence, it is available for students whose GPAs are not available. Table 3 shows data availability for select measures in the study.

Research Questions

This study centers chiefly around three research questions, all of which center around students in the UBMS program during the range specified in the data. Each question maintains its own role in providing a perspective regarding the effectiveness of the program. The first discusses program performance against ED-imposed measures and objectives. The others focus on data analyses between UBMS and its sister program as well as delve deeper to "look under the hood" of the UBMS program itself using Confirmatory Program Evaluation theory. Data analysis was conducted using the R statistical programming environment.

Table 3

Data Availability for Measures in the Study

Variable	Cohorts for Which Data are Available	Initial Student Pool
High School GPA	2016–2021	194
Proficiency in Math State Assessments	2008–2021	306
Proficiency in Reading/LA State Assessments	2008–2021	306
Postsecondary Enrollment	2008–2021	306
Employment	2016–2021	122
Community Service	2016–2021	122
Participation Level	2016–2021	122
Rigorous Course of Study	2016–2021	153
Advanced Math Courses	2013–2021	211

Research Question One: Assessing the Program's Own Objectives

First, the study considers the following research question: How do UBMS students perform in light of the program's own projected goals, as outlined in proposal documentation? It is fairly common for programs to set goals for themselves in order to gauge their levels of supposed success and effectiveness. Often, logic models illustrate the relationship between a program, its activities, and intended effects. Although the UBMS program at Temple has no logic model from which to guide its evaluative efforts, its stated objectives, described in its Evaluation Plan, help to steer the direction in which it moves and to structure its monitoring endeavors. In the application for funding, program leaders reference local, state, and national metrics, which assist in the deliberate crafting of objectives for program participants. In particular, its Evaluation Plan, specified in its most recent application cycle, lists a number of "ambitious yet attainable" objectives to which UBMS students must aspire (Curci, 2016, p. 63). Where suitable, findings will be juxtaposed with those on appropriate citywide and state levels.

Namely, the program seeks to measure its effectiveness by considering students' grade point averages and state assessments scores. It also gauges its sense of effectiveness based on students' high school retention rates and graduation rates. Not only does graduation matter, but whether students maintained a rigorous program of study in high school does, too. Finally, it measures postsecondary enrollment and completion and, specifically, if these students finished with a STEM major. In Chapter 4, the study explores basic statistical data using the R statistical programming environment.

Research Question Two: Comparing UBMS and UB on Select Data Measures

Second, the study considers the following research question: How do students in the UBMS program compare with those in the UB program regarding: 1) advanced math course completion, 2) high school state proficient achievement level in mathematics, and 3) postsecondary enrollment? Both programs thrive under the same leadership at Temple and have done so for the entire time in existence within the college. Irrespective of the three administrative periods in which the programs have been in effect, both the UB and

UBMS programs have operated side by side. One wonders if UBMS students outperform UB students on the referenced fronts, especially concerning those variables with a STEM focus. Investigating two of the three areas—advanced math course completion and secondary state assessment performance—provides a unique view into whether the UBMS program dedicates more of its resources into strengthening its STEM-focused participants more than it does its non-STEM ones in the UB program, given the missions of both.

In each of these three scenarios, the comparisons between the two programs depend on how data are stored for the program. In preparation for the study, the analyst was able to determine how data for categories were obtained and stored, though no access to the data was made available before the study was initiated. The analyst's access to Section II, the Record Structure for Participant List, was useful in that it conveyed how the data for each variable was recorded and stored. Since data is gathered as binary (i.e., success or failure) and nominal (i.e., categorical, unranked, and unevenly spaced), Pearson's chi-square test of independence becomes the method of choice for analyzing the three cases. Ultimately, one determines if pairwise comparisons of response ratios significantly differ between programs for each variable.

Of course, one may offer reasonable inferential predictions. For the two variables concerning math performance, one might assume that UBMS student performance would be significantly higher than that of UB students since the former program focuses more on STEM preparation for its students, in theory. For the variable regarding postsecondary enrollment, one might assume that there would be no significant difference between both populations since, at a minimum, both programs aim to increase the number of students that attend college despite choice of major. The chi-square tests are performed using R.

Research Question Three: Leveraging CPE to Assess the UBMS Model

The final research question takes a closer, more refined look at the interplay between select UBMS input variables and their ability to predict certain program outputs. The study addresses the following research question: How does the UBMS model in the study fare against scrutiny by the Confirmatory Program Evaluation (CPE) method of assessment? This more concerted research effort does not concern itself with comparing student performance with preset programmatic goals or with measuring against the UB program; this focus of this research endeavor attempts to take an introspective peek at the UBMS program and scrutinize components or services that may or may not be critical to its effectiveness. Although several methods may shed some light on this input-output interchange, the technique of Confirmatory Program Evaluation (CPE) provides a theory-driven basis for exploration in this instance.

The crux of the CPE methodology explores relationships between variables using a multivariate regression analysis model. Herein, a path analysis model is to be examined, which searches for path coefficients that offer information about the alleged effect that a predictor variable has on an allegedly related outcome variable. Various relationships among variables exist, none of which are guaranteed to reveal any useful details concerning outcome realities. The outcome variables, pointing toward a heightened interest in STEM, are UBMS students' achievement of a rigorous course of study and advanced course taking in high school. Although UBMS's program theory includes tracking students to discover if they major in STEM fields, this information serves as a more removed, distal outcome, likely lessening an argument of causal inference of the program's effectiveness. Further, the ideal UBMS model, according to the literature, would consider data on participants' initial STEM major upon arrival in college. Unfortunately, UBMS program leadership nationwide are not required to report such information to the ED.

The CPE method calls upon several steps through which causal discoveries concerning outcomes may arise. In sum, the steps are as follows:

1. Specify the program theory and processes affecting outcomes.
2. Identify and measure outcomes indexing various effects of participation.
3. Collect or utilize data on causal mediating factors of the program theory.
4. Test causal mechanisms to possibly explain outcomes.
5. Interpret the pattern of findings to facilitate generalization and knowledge transfer
6. Identify formative uses of findings for program improvement.

Although a number of causal mechanisms are available for analytical exploration, a path analysis model is explored in this study. The proposed model linking UBMS program ingredients and outcomes to be investigated is shown in Figure 8. Pointedly, the model focuses on students' obtaining a rigorous course of study and completing advanced math courses as study outcomes. Predictor variables are work study, employment, community service, level of program participation, and length of time students were

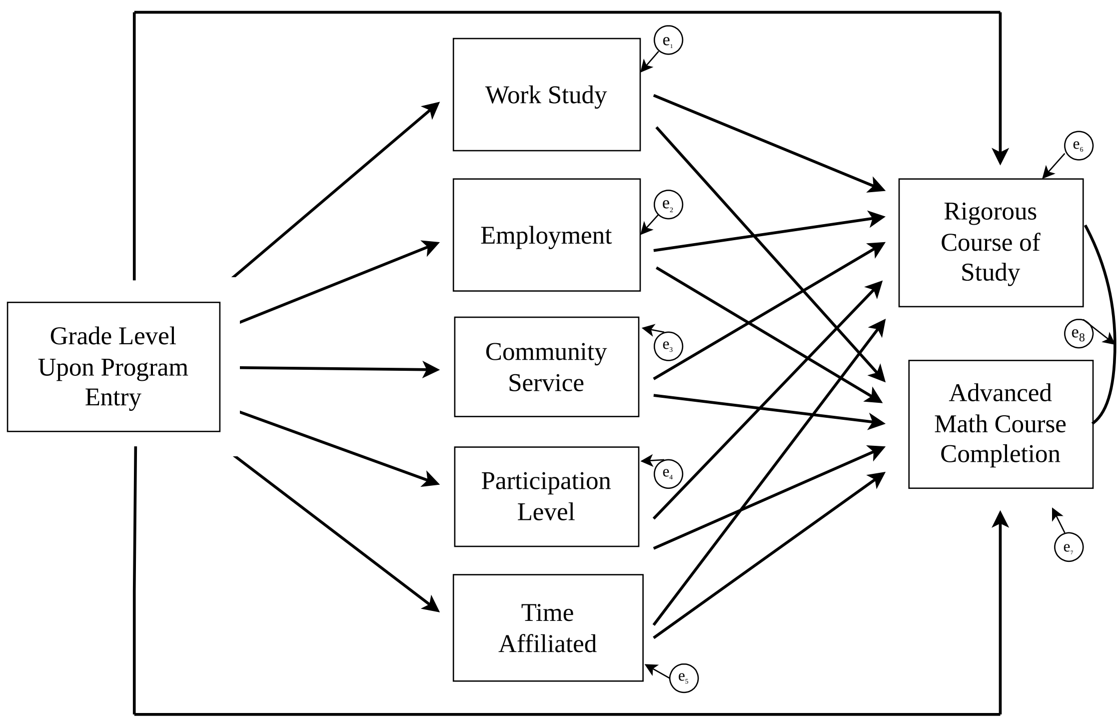


Figure 8. *Exploratory Path Analysis Model for Temple's UBMS Program*

affiliated with the program. The model investigates the following associations, where standardized path coefficients are carefully observed and interpreted:

$$Work = p_{GE}GE + e_{Work}$$

$$Employ = p_{GE}GE + e_{Employ}$$

$$Comm = p_{GE}GE + e_{Comm}$$

$$Part = p_{GE}GE + e_{Part}$$

$$Affil = p_{GE}GE + e_{Affil}$$

$$Rig = p_{GE}GE + p_{Employ}Employ + p_{Comm}Comm + p_{Part}Part + p_{Affil}Affil + e_{Rig}$$

$$Adv = p_{GE}GE + p_{Employ}Employ + p_{Comm}Comm + p_{Part}Part + p_{Affil}Affil + e_{Adv}$$

Standardized coefficients offer some insight regarding direct or mediating effects, which may provide some understanding with respect to possible causal inference. Coefficients will enlighten the analyst regarding which independent variables tend to predict students' obtainment of a rigorous course of study and their enrollment in advanced math courses.

Findings may help to corroborate or refute the program's claims of effectiveness in relation to the predictors in the study. Path analytic coefficients will assist the researcher in the investigation of relationships between all predictor variables and outcome variables presented in Figure 8. Subsequently, what does the model suggest with regard to causality, according to Reynolds' CPE theory? Which, if any, of the theory's six criteria for causality does the model appear to meet? A dive into performing the path analysis and using Reynolds' causal framework would assist greatly in the discussion of the UBMS program and investigate its sense of accomplishment.

Finally, on a wider scale, what implications do the findings suggest with regard to educational leadership? What insight may be provided to districts, principals, and other leaders regarding their relationship and partnership with surrounding universities with respect to STEM intervention for students? Which UBMS "ingredients" are essential in making an impact in the academic lives of these students? What implications exist regarding alliances between principal investigators, program administrators, and statisticians who evaluate initiatives like UBMS? A reasonable analysis may shed some light on these matters and offer sensible inferences from findings.

CHAPTER 4

RESULTS

Herein, the study addresses each of the research questions, offering statistical analysis and interpretation. Particular analysis techniques or methods do not stand alone when interpreting data; however, they play limited yet valuable roles in their own unique way, complementing each other to tell a unified story. Presented results, then, only provide analysis and discussion from one vantage point, which should be corroborated using alternate but equally valid methods. As such, an analysis and discussion of results for the three stated research questions hold center stage in this chapter.

Research Question One: Assessing The Program's Own Objectives

The ED has established for each host of the UBMS program certain ambitious yet attainable objectives on which to focus as related to student performance. Although these objectives are uniform across program host centers and/or universities, individual program leadership affixes its own agreed-upon percentages of success for each objective within the program application for funding. Each program is expected to set goals and work toward promoting student excellence in the following areas: grade point average, achievement on standardized test scores, school retention and graduation, rigorous course of study completion, postsecondary enrollment, and postsecondary completion.

Grade Point Average

At Temple, the UBMS program leadership has stated in the applications overlapping the years of available APRs that "70% of participants served during the project year will have a cumulative GPA of 2.5 or better on a four-point scale at the end of the school year" (Curci, 2016, p. 12). GPA data is available mostly for participants who have remained in the UBMS program through graduation, secured a regular secondary diploma and been assigned to a PSE cohort between 2016 and 2021. A small percentage included students who graduated from high school but did not pursue secondary education anywhere (or possibly started after a one-semester deferment). Thus, a total of 194 students are included in the unweighted GPA pool.

Sometimes, weighted GPAs are not available, so unweighted GPAs provide the best information for analysis. In this case, GPAs are unavailable or unrecorded for 29 students, resulting in available unweighted GPAs for 165 UBMS students. The data reveal that the average unweighted cumulative GPA for UBMS students in this study is 3.51. There were 160 participants whose unweighted GPA exceeded the program's goal of 2.5. Respectively, these numbers represent 97% of the participants, bettering the program's metric (70%) for this specific objective.

Proficiency on State Assessments

UBMS program leadership at Temple has established a goal in which "50% of UBMS seniors served during the project year will have achieved at the proficient level on state assessments in reading/language arts and math (Curci, 2016, p. 13). Goals set for the grant cycle coinciding with students' participation represent the program's success mark related to student performance on state assessments. These exist as relative measures of evaluation, which give a broader sense of achievement beyond the world of UBMS and the surrounding Philadelphia area.

Although GPA information is unavailable for students in PSE cohorts prior to 2016, state assessment information is available for these same individuals. Hence, data for both the math and reading/language arts assessments come from across the entire range of 2008–2021 students. A total of 306 students constitutes the entire pool from which data on this variable are possible. Data on state assessments in reading and language arts are available for 267 students; in math, data are available for 283 students. There are 24 students for which the reading and language arts results are unknown and 15 cases where students either had not taken the assessment yet or results were not yet available; there are 17 students for which math results are unknown and 6 cases where students either had not taken the assessment yet or results were not yet available.

For data reported on the reading and language arts assessment, 238 students achieved the level of proficiency, resulting in approximately 89% of UBMS graduates who obtained such an accomplishment, as indicated during the time period covered in the available APRs. A total of 230 students achieved the level of proficiency on the math assessment, resulting in a success rate among UBMS graduates of roughly 81% during the same period. Naturally, both values exceed the 50% threshold set by program leadership. Accordingly, the City School District of Philadelphia reports an average reading proficiency score of 46% and an average math proficiency score of 35%; the average proficiency scores for math and reading in the state of Pennsylvania both hover at 48% (Public School Review, n.d.).

High School Retention and Graduation Rates

With respect to retention and graduation, UBMS leadership at Temple projects that "85% of UBMS project participants served during the project year will continue in school for the next academic year, at the next grade level, or will have graduated from secondary school with a regular secondary school diploma" (Curci, 2016, p. 15). A plethora of factors play into whether a student continues on the road to graduation. The ED, in its 2021–2022 publication summary, noted a number of reasons that students in Pennsylvania failed to finish high school, including academic problems, behavior problems, desire to work, and a basic dislike for school in general (Pennsylvania Department of Education, 2023).

Directly or indirectly, data on all students who had an affiliation with the UBMS program at Temple are available with respect to retention in high school. Information is provided for those who severed ties with the program after receiving servicing. Accessible data corroborate that none of the students stopped short of high school graduation, as none of the reasons listed for students' eventual non-affiliation with the program involved dropping out of high school (i.e., Reason #3 in Field 46). For affected students, reasons for leaving the program include the following: the need or desire for employment, relocation out of the target area, other extra-curricular activities, lack of interest in the program, graduation from high school, and dismissal for not meeting the program's conduct standards. Although these students may still, in theory, drop out of high school after leaving the program proper, no direct indication of such exists from the data.

In comparison, the 2020–2021 school term in Philadelphia witnessed an on-time, four-year graduation rate of 75.4% (ORE, 2023). In Pennsylvania, the 2022 graduation rate was an impressive 95.89%, second only to Massachusetts's, which was only 0.21% higher (*High school graduation by states*, n.d.). Thus, a 100% graduation rate is especially unique for the students in this program during the period of study.

Rigorous Program of Study in High School

Not only does graduation matter, but students' maintenance of a rigorous program of study in high school does, too. As its goal, UBMS program leadership at Temple projects that "80% of all current and prior year UBMS participants who graduated from high school during the school year with a regular secondary school diploma will complete a rigorous secondary school program of study" (Curci, 2016, p. 16). One recalls that the criteria for a rigorous course of study are various and are defined herein in the Measures section (chapter 3). Data for a sample of 123 students apply for this variable. Earlier APRs, not in the analyst's possession, contain data for cohorts earlier than 2016. Data is unknown for eight students. A total of 101 students graduated high school with a regular secondary school diploma and completed a rigorous secondary school program of study, yielding an 88% success rate. These data include analysis for participants who were in high school during the pandemic. This reported rate exceeds the projected objective of 80%.

Postsecondary Enrollment

Further, UBMS leadership has continued to set objectives concerning participants' postsecondary enrollment. Although it may be difficult to keep up with students' progress throughout their postsecondary journey, the ED expects program leadership to document students' initial decision regarding academic life after high school. The first priority is to keep track of UBMS graduates who have enrolled in postsecondary programs of study, including the pursuit of an associate or bachelor's degree. Program leadership projects that:

> 50% of all current and prior UBMS participants who graduated from high school during the school year with a regular secondary diploma will enroll in a program

> of postsecondary education by the fall term immediately following high school graduation, or will have received notification by the fall term immediately following high school from an institution of higher education of acceptance but deferred enrollment until the next academic semester (e.g., spring semester). (Curci, 2016, p. 17).

The pool of students from which this information is mined has a sample size of 306. As with reading/language arts and math assessments, these are all of the distinct students who have participated in the program within the 2008–2021 window. One wonders what percentage of these students immediately went on to pursue postsecondary studies after high school. As stated, students who received notification of postsecondary acceptance but postponed for a semester—mainly because of the initial height of the pandemic—are included in the success count.

According to the data, 273 students completed their high school educational journey with either a regular or non-regular high school diploma. Of this, the data disclose that 18 of them did not enroll in any program of postsecondary education, and information is unknown for 15 of the students. Hence, approximately 93% of the students graduated and enrolled into some type of postsecondary education immediately following high school graduation. Statewide, 61.9% of 2018 students in Pennsylvania enrolled immediately into college after graduating high school, while 63.65% reached this standard nationwide (National Center for Data Statistics, 2023).

Postsecondary Completion

Data reveal that several students were currently enrolled in a postsecondary program of study at the time that information was collected for a particular year's APR. After a period of six years, UBMS program leadership has gathered information pertaining to the objective of completing either the associate or bachelor's degree. For these postsecondary criteria, program leadership has projected that at least:

> 50% of participants who enrolled in a program of postsecondary education, by the fall term immediately following high school graduation or by the next academic term (e.g., spring term) as a result of acceptance by deferred enrollment, will attain either an associate or bachelor's degree within six years following graduation from high school. (Curci, 2023, p. 19)

This ratio is derived from a longitudinal perspective spanning a six-year window. In other words, one needs to be able to obtain a completion ratio using data from students' high school graduation year (i.e., PSE cohort) and six years in the future, as this is the time period within which the program gauges this measure. Data are available for UBMS graduates who belong to PSE cohorts 2011 through 2015 and then for the same cohort groups for postsecondary completion years 2017 through 2021, respectively.

For example, 22 UBMS students finished high school in 2015 (i.e., 2015 PSE cohort). Eleven of them attained either an associate or bachelor's degree within six years following their graduation, yielding a 50% postsecondary completion rate, which is highlighted as such for the year 2021 in Figure 9. Although rates in the near past had been on a steady increase, the percentage dipped to the aforementioned rate in 2021. Though low, it still meets the proposed rate of achievement set by program administrators for that measure.

In each of the explored seven cases, a different and unique sample was used to determine actual percentages when compared to projected ones. Referred to as incomplete cases, these values provide one lens through which to view and analyze the data. Having shifting samples can mislead one's interpretation or increase a sense of bias

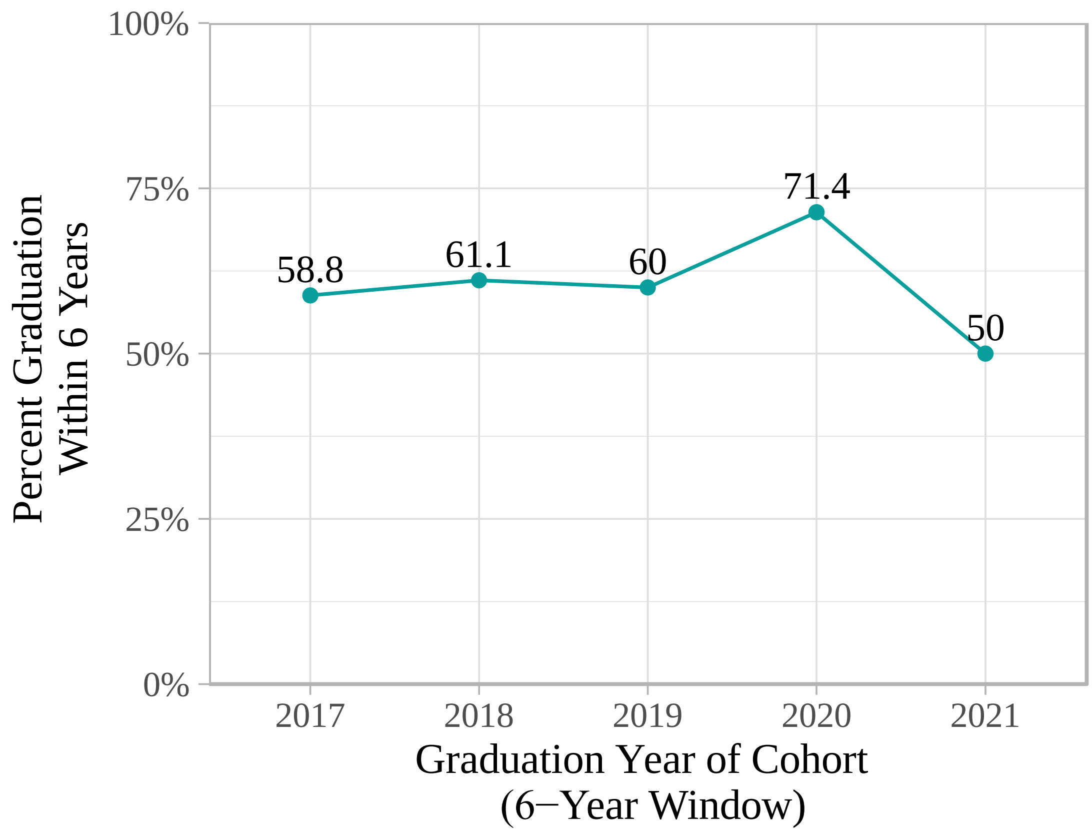


Figure 9. *UBMS Postsecondary Completion Percentages, 2017–2021*

of the results if data appear to be missing in a non-random way. Variable samples using these incomplete data range from 115 students to 324 for this research question, depending on which variable is considered at the moment. Each of the separate samples helps determine actual percentages for the analysis.

One may further consider the same analysis of the data but only using complete data (i.e., data omitting any students without information for all variables that are being explored). Since variables for school retention and postsecondary completion are referred to and analyzed differently in the projected-to-actual comparisons, they are not included in the mix for determining sample size for the complete dataset. As such, a total of 81 students comprises the complete sample and serves as the basis for comparison for all variables in this more uniform analysis. In other words, all 81 of these students possess data for each of the variables being explored—except retention and postsecondary completion—for this research question; students with missing data in at least one of these variables is omitted for these complete cases.

Table 4 summarizes these ED-based projected rates and Temple's incomplete and complete actual rates across program objectives. When observing results using both incomplete and complete data, differences are mostly small. The largest difference, for the variable of rigorous course of study, is only four percentage points. The closeness of percentage points for all incomplete-complete variable comparisons suggests that the missing data in the incomplete cases are rather random and cause no huge evaluative stir when measured up against the program's projected success rates.

Research Question Two: Comparing UBMS and UB on Select Data Measures

Students in the UBMS and UB programs have maintained an amiable relationship on Temple's campus. Run by the same administration, both programs cater to similar student demographics, as they both service FLGI students and must meet the same guidelines regarding student participation. Notably, since both serve students in the Philadelphia area, one is not surprised that demographics of both programs do not differ significantly from each other. Their composition is virtually the same across categories. Figure 10 corroborates this notion, as it offers a rough glance at both programs and their general make-up. With respect to programming, UBMS offers a more focused student path, eyeing toward careers in STEM. Students engage more in activities during the year geared toward these fields. Such activities include, but are not limited to, taking more STEM coursework, tutoring, and campus visits to universities known for STEM.

Table 4

Department of Education Standard Objectives for the UBMS Program: Projected versus Actual Rates, 2008–2021

Objective	Temple's Projected Success Rate	Temple's Actual Success Rate (Incomplete Samples)	Temple's Actual Success Rate (Complete Sample*)
Grade Point Average	70%	97%**	96%**
Proficiency in State Reading/LA Assessments	50%	89%	89%
Proficiency in State Math Assessments	50%	84%	81%
School Retention and Graduation	85%	100%***	100%***
Rigorous Program of Study	80%	88%	93%
Postsecondary Enrollment	50%	93%	94%
Postsecondary Completion	50%	See Figure 9	See Figure 9

*$n = 81$
**Unweighted GPAs
***Based on loose inference from data

With respect to student performance between the UBMS and UB programs, the analyst finds particular value in the investigation of three variables found in the data. It becomes of interest to discover what statistical realities may be inferred from testing to discover if differences between said student performances exist and what they may imply concerning program functionality and effectiveness for UBMS students. More pointedly,

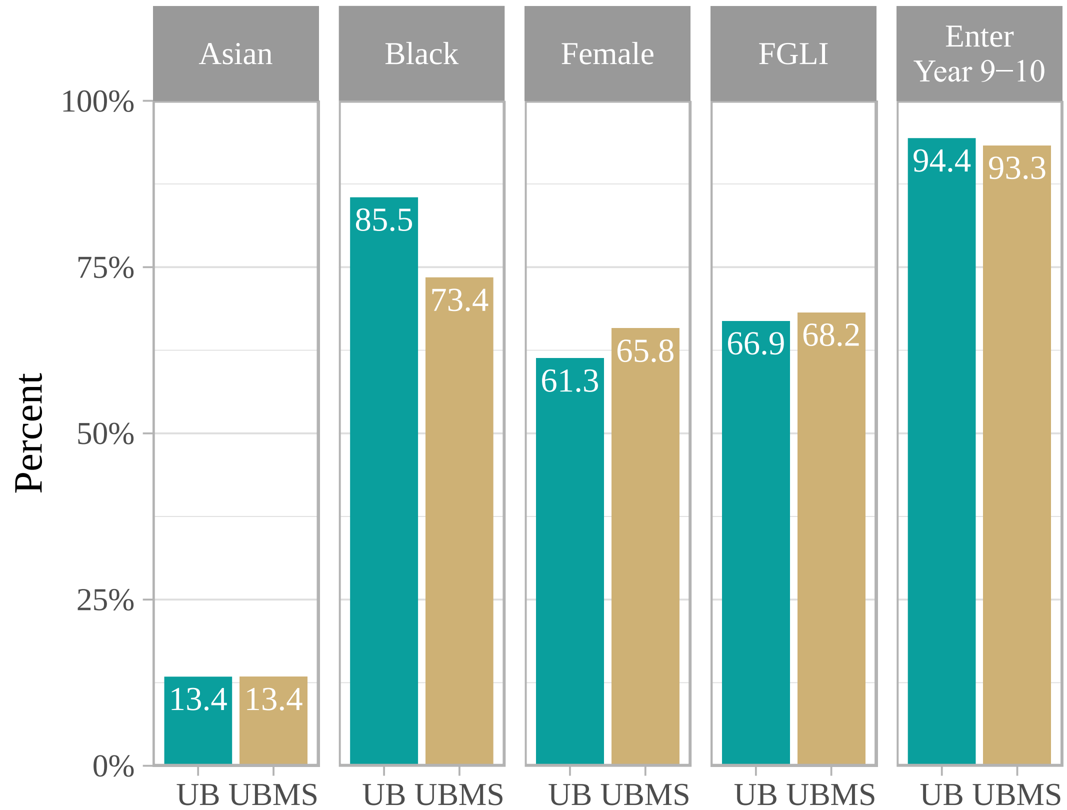


Figure 10. *Temple's Upward Bound and Upward Bound Math and Science Programs at a Glance*

probing to highlight any significant differences in three cases may shed some light on if program leadership should reconsider its strategy and funneling of resources to UBMS participants, perhaps resulting in increased performance along the STEM journey. All cohorts are considered together, without giving attention to between-cohort comparisons. It is statistically possible for cohorts in UB to outperform those in UBMS if one were to analyze in such a detailed manner by cohorts. The three areas of emphasis in this research question, however, seeks to reveal percentage comparisons as a whole between groups during the APR periods of focus. Emphases center around comparisons between the following variables: advanced math course completion, state proficiency levels on math assessments, and postsecondary enrollment.

Advanced Math Course Completion

Given the program's mission, one may wish to discover how prepared students are with respect to their math courses. Studies echo the fact that measuring whether students enroll in advanced math courses is often a telltale sign of increased interest in postsecondary education and, often, is the gateway to a pursuit of STEM majors and careers (Alvarado & Muniz, 2018; Warne et al., 2019; Sadler et al, 2014). One is reminded that "advanced math courses" means that participants completed two years beyond algebra 1 during their high school career. Since both UB and UBMS programs are run by the same staff at Temple, some may wish to determine if there is a significant difference in the proportion of students taking advanced math courses in the UBMS program compared to the UB program. As the mission for the UBMS program is to equip its students with the best preparation in which to pursue a STEM degree, one may surmise that students in that particular program may take such courses at a higher rate than those in the other.

For this study, data reveal percentages for those in the UB and UBMS programs with respect to students who completed referenced advanced math courses. Data does not reveal at what point students attain such; however, records indeed show that students did or did not take said courses by the time they finished high school. For this variable, no data is available for students whose cohorts predate 2012. Figure 11 highlights this comparison of percentages.

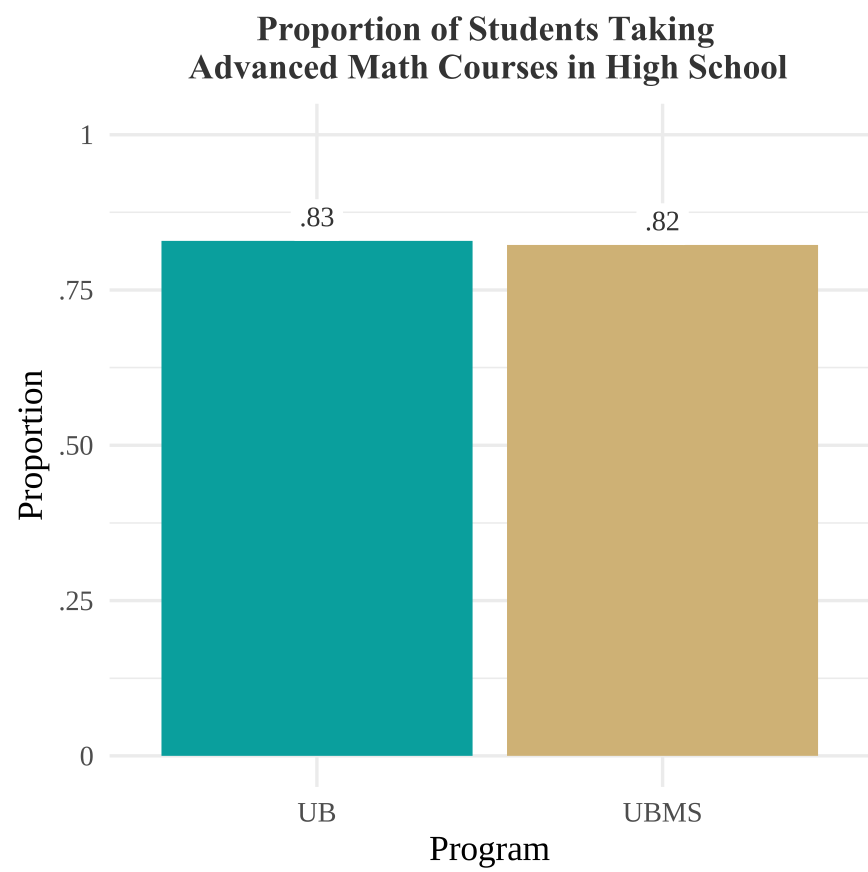


Figure 11. *Proportion of Students Taking Advanced Math Courses in High School*

A glance at a summary of the raw data is viewable in a 2 × 2 contingency table for the variable of advanced math courses. Perhaps surprisingly to some, the percentage of UBMS students taking these advanced courses is lower than that of UB students, in terms of raw percentages. One might have surmised that, since the mission of the UBMS program is to equip its students in all things STEM related, these students would have yielded a larger percentage for this variable than their non-STEM counterparts. This is not the case, however. Table 5 offers further details about this comparison.

Table 5

Advanced Math Courses: Observed and Expected Frequencies

	Observed Frequencies *Advanced Math Courses*		
Program	Completed	Not Completed	Total
UB	188	39	227
UBMS	139	30	169
Total	327	69	396

	Expected Frequencies *Advanced Math Courses*		
Program	Completed	Not Completed	Total
UB	187.447	39.553	227
UBMS	139.553	29.447	169
Total	327	69	396

$\chi^2 < .001$, $p = .99$ *(not significant)*

Yates' continuity correction in the reported test statistics is integrated to reduce errors that come from using a 2 × 2 table, possibly resulting in a smaller *p*-value than expected (Kishore & Jaswal, 2023). Results reveal that there is no association between students' program and whether or not they completed advanced math courses. Hence, there is no significant association between the programs when one considers whether students completed advanced math courses. Although there exists a difference in the raw percentages, the differences are not statistically significant. Essentially, UB and UBMS graduates complete advanced math courses in high school at an equal rate. Students in neither program complete such courses at a significantly higher rate than students in the other.

Proficiency Status on State Math Assessments

Observing students' performance on state math assessments provides some reflection on how the program seems to influence students' academic performance beyond classroom borders. It bears mentioning that reaching a level of proficiency on the math assessment (i.e., Keystone Exam in Algebra) has been a statewide graduation requirement for Pennsylvania students since 2017. Only since 2023 have students benefited from legislation that allows for alternate ways of demonstrating proficiency in math, including satisfying approved requirements based on grades in certain courses. Even still, a head-to-head comparison of both programs may be of use to program leadership as they take stock and reflect on how their students fare in light of these state-set thresholds.

Data reveal percentages for those in the UB and UBMS programs with respect to students who attained the level of proficiency on state math assessments. According to APR instructions on data collection on this topic, once students achieve the level of proficiency, they attain it once and forever. For example, if a student achieves proficiency during his or her sophomore year, the same status carries forward through to high school graduation. The student is not expected to prove proficiency in math again at a later grade level. Figure 12 shows the percentage of students in this study who achieved proficiency in math across both programs.

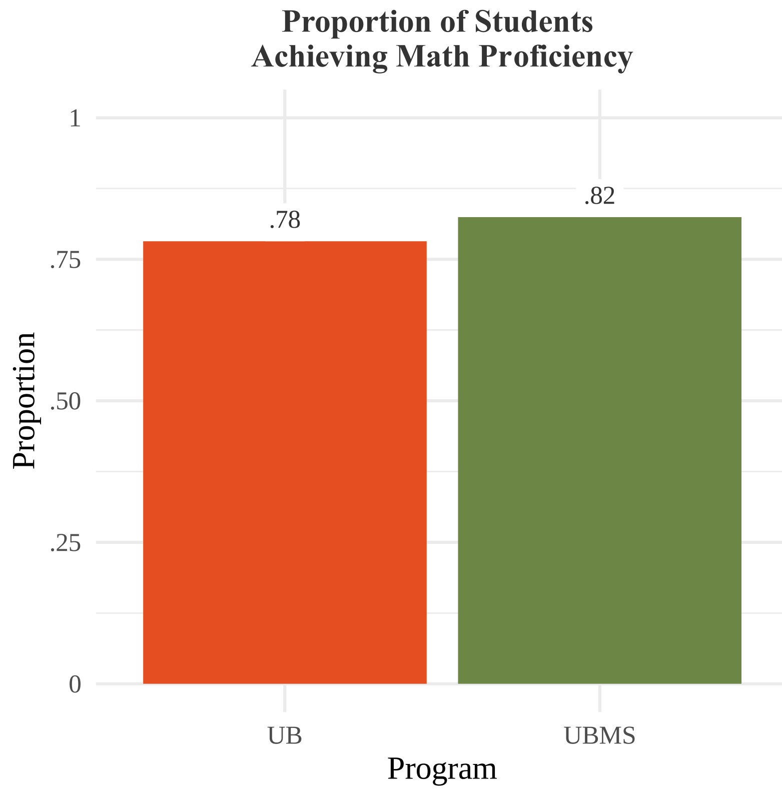


Figure 12. *Proportion of Students Across Programs Achieving Proficiency on State Math Assessments*

One hypothesizes that there exists an association between students' program and whether or not they reached the level of proficiency in math on state assessments. Table 6 highlights results. Hence, there is no association between students' program and whether or not they reached the level of proficiency on math state assessments. There is no significant association between program participation and whether students achieved a level of proficiency. Essentially, when it comes to state assessments, UB and UBMS graduates achieve the level of math proficiency at equal rates. Students in neither program achieve such proficiency at a significantly higher rate than those in the other.

Table 6

Proficiency on State Math Assessments: Observed and Expected Frequencies

Observed Frequencies

	Math Proficiency		
Program	Proficient	Not Proficient	Total
UB	215	60	275
UBMS	230	49	279
Total	445	109	554

Expected Frequencies

	Math Proficiency		
Program	Proficient	Not Proficient	Total
UB	220.894	54.106	275
UBMS	224.106	54.894	279
Total	445	109	554

$\chi^2 = 1.33$, $p = .25$ (not significant)

Postsecondary Enrollment

Arguably, the most important goals of both UB and UBMS programs are the enrollment of students into postsecondary education and the finishing of the same degree within six years; for UBMS students in particular, program goals pivot to include students' attainment of the postsecondary degree but with a STEM focus. Although technically outside of both programs' control during this period, students continue to be tracked and data updated during postsecondary years as much as possible. At this stage, the program is able to wield very little influence over students in the direction of their postsecondary education and beyond. Measures to monitor student progress are in operation, and program managers must make a sustained effort to monitor students during the next six-year period. This variable indicates if students completed high school and started a postsecondary program, including an occupational/educational program, an associate's program, or a bachelor's program. Figure 13 illustrates percentages for students in both programs who went on to pursue postsecondary education in some form following their high school career.

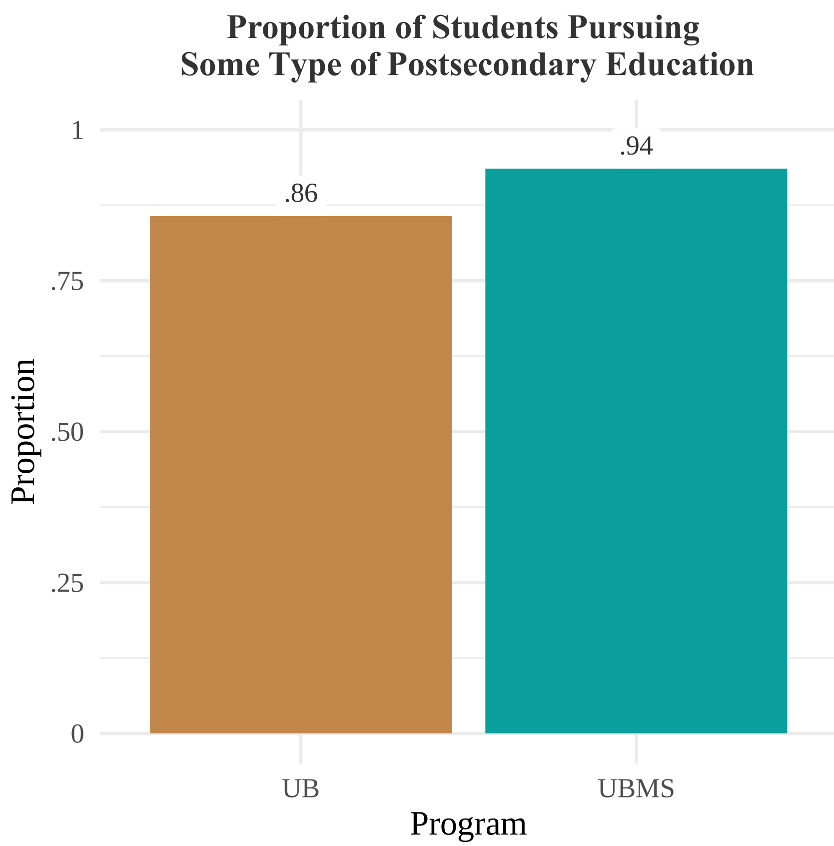


Figure 13. *Proportion of Students Beginning Postsecondary Education Immediately Following High School*

One assumes that an association exists between students' program and whether or not they pursued postsecondary education immediately after high school. Table 7 highlights results.

Table 7

Initial Postsecondary Enrollment: Observed and Expected Frequencies

Observed Frequencies

	Initial Postsecondary Enrollment		
Program	Enrolled	Did Not Enroll	Total
UB	293	47	340
UBMS	273	18	291
Total	566	65	631

Expected Frequencies

	Initial Postsecondary Enrollment		
Program	Enrolled	Did Not Enroll	Total
UB	304.976	35.024	340
UBMS	261.024	29.976	291
Total	566	65	631

$\chi^2 = 9.72, p = .002$ *(significant)*

Thus, there is an association between students' program participation and whether or not they pursue postsecondary education immediately following high school. Thus, the rate at which students pursue such depends on which program they are in. Essentially, those who come through the UBMS program tend to pursue postsecondary education at a significantly higher rate than their UB counterparts.

In sum, when comparing the UBMS program with the UB program across select variables, one observes instances in which both programs yield virtually similar results among students and one in which they significantly differ. Arguably, variables for which results are similar are those that analysts might expect UBMS students to stand out in a significant way. UBMS program leaders might consider ways in which to work with public school leadership to provide greater support to its UBMS clientele with respect to increasing the number of students reaching proficiency on state math assessments and completing advanced math courses. Since the focus of the UBMS program is to lean heavily into math and science preparation for its students, implementing programmatic strategies on students' high school campuses during the academic year may encourage more participants to enroll in such advanced math courses, thus possibly increasing the likelihood of reaching proficiency in math on the assessments. Table 8 summarizes these UB-UBMS comparisons across select variables in the data.

Table 8

Comparative Results on the UB and UBMS Programs Across Select Variables

Observed Variable	Hypothesis Decision	Interpretation
Advanced Math Course Completion	Hypothesis not supported	Students show virtually similar results.
Proficiency on State Math Assessments	Hypothesis not supported	Students show virtually similar results.
Postsecondary Enrollment	Hypothesis supported	UBMS students enroll at a significantly higher rate than US students.

Research Question Three: Leveraging CPE to Assess the UBMS Model

The Confirmatory Program Evaluation (CPE) methodology is preferable with UBMS analysis because the data under investigation satisfy a number of technique-specific criteria; particularly, data are quasi-experimental (i.e., no controls), longitudinal, and in the postprogram stage (Reynolds, 1998). CPE's mission here is to methodically assess the UBMS program by attempting to clarify the presence or absence of program "ingredients" that lead to program results. To some degree, the technique is poised to "strengthen causal inference through systematic investigation of the nature of the relationship between treatment and outcome" (p. 207).

Revelations from application of the method may do well to inform UBMS program leaders with the knowledge needed for updating or adjusting program offerings; further, as students are also serviced throughout the school term at their native high schools, results may inform program leaders in their partnership with public school leaders of best practices to implement to maximize student success. Implementation of CPE involves six major steps, which are explored hereafter; each stage in the procedure is delineated and supported by Reynolds (1998). From specifying the program theory to identifying formative uses of findings for program improvement, the CPE recipe of assessment provides a unique and relatively unbiased framework for testing program efficacy. Although alluded to in Research Questions One and Two, a few of the initial steps are recounted expressly in the CPE methodology for the sake of clarity and thoroughness.

1. Specify Program Theory and Processes Affecting Outcomes

The UBMS program theory is reiterated here; it is that FGLI students' fitness for college entry—and for later success in STEM careers—will be made easier through sensible academic intervention, mentorship, and various other supportive activities. Summarily, early and sustained intervention on several fronts may level the educational playing field for FGLI students and may provide them with the tools necessary to persist in STEM. Through the offering of relevant program services—including summer programs, counseling throughout the year, computer training, financial literacy training, and faculty-guided research—the goal is to "help students recognize and develop their potential to excel in math and science and to encourage them to pursue postsecondary degrees in math and science, and ultimately careers in the math and science profession" (U.S. Department of Education, 2023b).

Several hypotheses undergird the program effects that will be tested. Primarily, the theory of program dosage provides the hugest rationale for including a few of the variables in this study. Additionally, the theory supporting the stance that relevant experiences outside of an academic context (e.g., internships and community service) may do well to strengthen students' academic base and hunger for STEM is well founded (Burgin et al., 2015; Salto et al., 2014; Singh et al., 2007; Witzel et al., 2020). Previous studies have demonstrated that various measures are associated with outcomes for programs like UBMS. More pointedly, past research supports an investigation of the following measures as related to their possible association with UBMS effectiveness: grade level in which students began the program (Rozek et al., 2019), student participation level (i.e., summer only, summer and academic year, etc.) (Reynolds, 1998), apprenticeship experiences (Burgin et al., 2015; Salto et al., 2014), student employment (Singh et al., 2007), participation in community service (De Los Rios et al., 2023), and overall length of time students remained in the program (Reynolds, 1998).

2. Identify and Measure Outcomes Indexing Various Effects of Participation

The key measures to assess UBMS goals could conceivably be many, several of which might include postsecondary enrollment, college major choice, rigorous course of study, and decision to enroll in advanced math courses in high school. Once students complete the program, UBMS influence becomes less significant; hence, outcome variables like postsecondary graduation rates and eventual college major become more distal in nature. Ideally, the more proximal outcome is initial postsecondary major declaration upon college entry. This would provide the last snapshot of student STEM interest in relation to participation in the program. Unfortunately, this information is no longer collected by UBMS programs.

As stated in chapter 3, relevant proximal outcomes herein pointing toward a heightened interest in STEM are UBMS students' attainment of a rigorous course of study and the completion of advanced math courses (Warner et al., 2019; Salto et al., 2014). Such measures tend to be early indicators for whether students choose postsecondary STEM majors and persist in STEM fields after college.

3. Collect or Utilize Data on Causal Mediating Factors of the Program Theory

A Unique Student Subset. At this point in the analysis, it becomes necessary to filter out students who stopped short of pursuing postsecondary education. Although the model does not focus on outcomes concerning postsecondary enrollment or decision on choice of major, it is still meant to focus in on students who indeed decided to pursue such. Outcomes explored, then, are investigated in light of predictors for students who made the move to extend their education in some type of postsecondary capacity. Many students entered the program at varying grade levels and remained through their high school graduation. They graduated from high school during the academic year with a regular secondary diploma and enrolled in college by the fall term immediately after graduation or the following spring through deferred-enrollment acceptance; a few did not.

Referencing this cadre of students at this moment in the study intersects with how the program itself monitors students' eventual success after high school. Once students successfully graduate and pursue postsecondary education, they are granted a postsecondary education enrollment (PSE) cohort year assignment and tracked beyond high school years. The PSE-cohort criterion is the filter established by the national program protocol, which informs its objective concerning students' postsecondary progress and completion and, indirectly, its possible effectiveness as a program. Hence, students who do not meet this particular criterion of postsecondary activity are excluded from this phase of the analysis. Figure 14 presents this student remnant within each PSE cohort. Data is only available for students in PSE cohorts 2016–2021. Hence, a total of 110 UBMS students fit this criterion within the key period of investigation in the study, providing the basis for the crux of inferential analysis hereafter.

Figure 14. *Upward Bound Math and Science Students by PSE Cohort Year, 2016–2021*

And Figure 15 shows a similar breakdown of this more refined subgroup. Again, data for all analysis to follow are only available for cohorts 2016–2021. Not all excluded students failed to pursue postsecondary education, though. This subgroup is comprised of 264 fewer UBMS students than those in the entire data referenced in Figure 7.

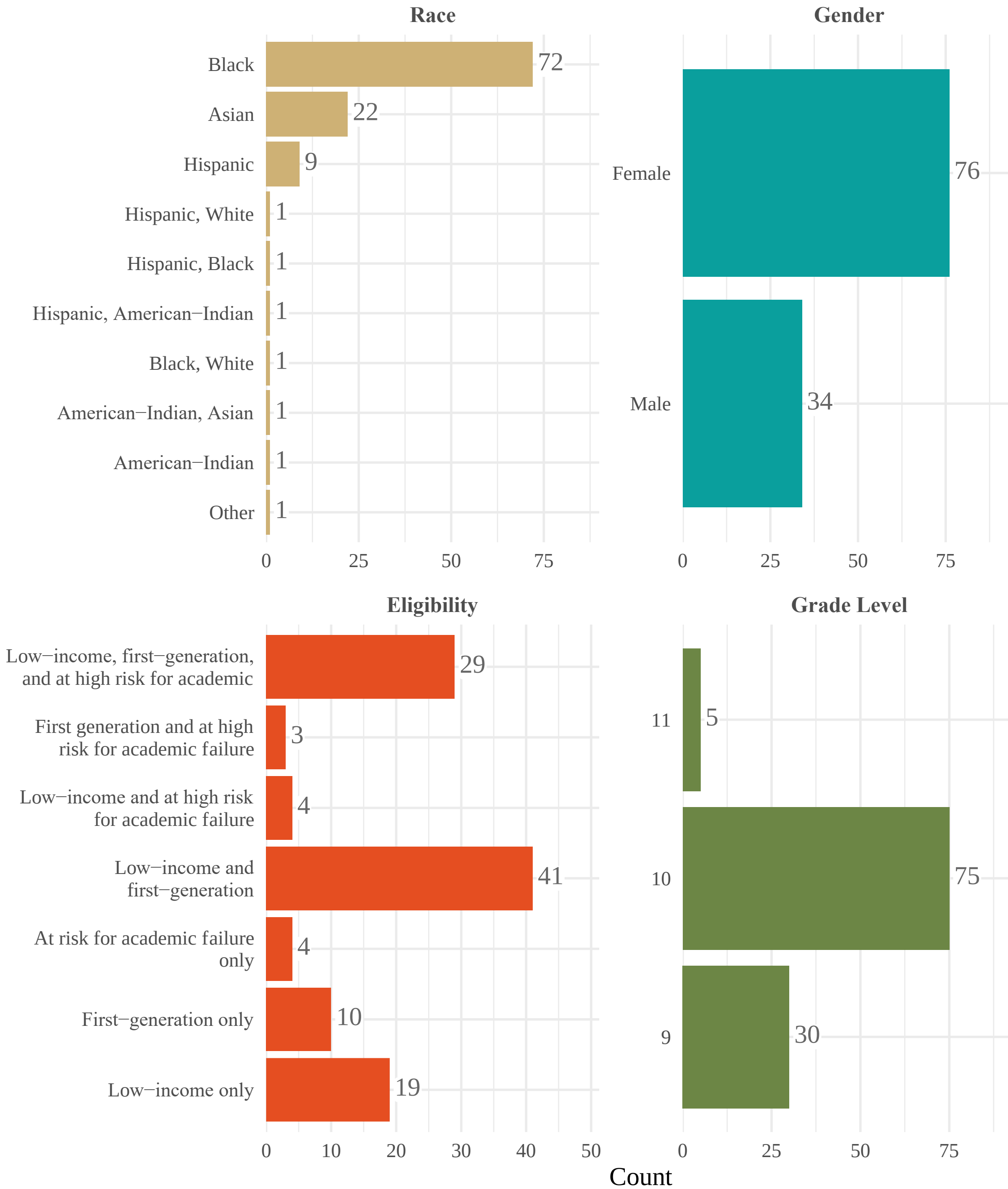


Figure 15. *Upward Bound Math and Science PSE Cohorts At a Glance, 2016–2021*

A little over 65% of this subgroup are Black. More than half are females. About 64% of the participants were identified as low-income and first-generation students upon their entry into the program; in the chart on program eligibility,

these students were classified as low-income and first-generation (41) or low-income, first-generation, and at high risk (29). As in Figure 7, an overwhelming majority of the students in these cohorts entered the program as rising tenth graders; none of them, however, entered the program during the summer between their eighth- and ninth- grade years, another noticeable distinction between data shown in Figure 7.

Data Collection. What makes the UBMS program unlike many others like it is its requirement to conform to standards as they relate to data collection and record keeping. As mentioned, data categories are already established by the ED. Program leaders collect and utilize such prescribed data at a minimum and report it on a yearly basis. Having to report yearly to the funding agency highlights the program’s internal accountability, thus guaranteeing a relatively strong sense of data accuracy. Instances of widely reported inaccurate data result in the retraction of funds. This is not to suggest that data collection and record keeping are error free. Though data categories are nonnegotiable, data collection in some categories may still convey some sense of subjectivity based on how different leadership may interpret it. For example, to determine if students exhibit low educational aspirations or show lack of confidence, self-esteem, and social skills, program leaders at one institution may use different instruments to assess than those at another. This may contribute to some level of variation in program data across host institutions.

Herein, one is not particularly concerned with this issue of subjectivity since predictive variables in this study are rather straightforward. However, because there is no set guideline for determining cutoff dates for length of time spent in an aspect of the program, for instance, some objectivity for this variable may be sacrificed. Further, whenever data is collected and maintained by humans, some degree of error may occur because of incorrect manual data entry. UBMS leadership has disclosed its plans for adopting software which makes data collection easier, especially when beginning and ending participation dates are involved for various programmatic services. No longer will staff have to roughly estimate dates of interest concerning students. Software will organize major program benchmarks and organize students' participation (or lack of it) to better chart data concerning relevant measures.

Data Recoding. To prepare the data for analysis, a bit of recoding was necessary. Several pieces of data within a given variable reflected the notion of being outdated for a specific dataset. Data for any given variable in an APR very well may have become outdated for specific students, depending on their PSE cohort. Depending on the variable, some data for students carried over for four years and fizzled out, becoming a "9" in subsequent APRs. Other variables provided obsolete or unknown data after six years. Recoding allowed for such extraneous information to be filtered in a systemic way. As a result, data was restructured for all predictor and output variables in the proposed UBMS models for relative data uniformity, for the handling of inconsequential data, and for eventual clarity of analysis.

Special attention was needed for the variables of Community Service, Employment, and Program Participation Level. Students may have been involved in community service activities for some years and not others. A mutation of data was necessary to account for this reality. For example, if a student participated in community service every year in high school except for her senior year, then her community service data value became 0.75, representing that she participated three-fourths of the time of her high school enrollment. This provided an overall objective sense of service over the four-year period. The same transformation was made for employment and program participation level. So that analysis could focus only on relevant data for the analysis, a data dictionary was developed to reflect an updated assignment of numbers to meanings, which would be more amenable to R's processing. Since most of the remaining data was binary in nature, the following assignments generally resulted: a "1" for Yes, a "0" for No, and the value of "NA" for the remaining options. Such NA values played no role in the analysis and were noted accordingly.

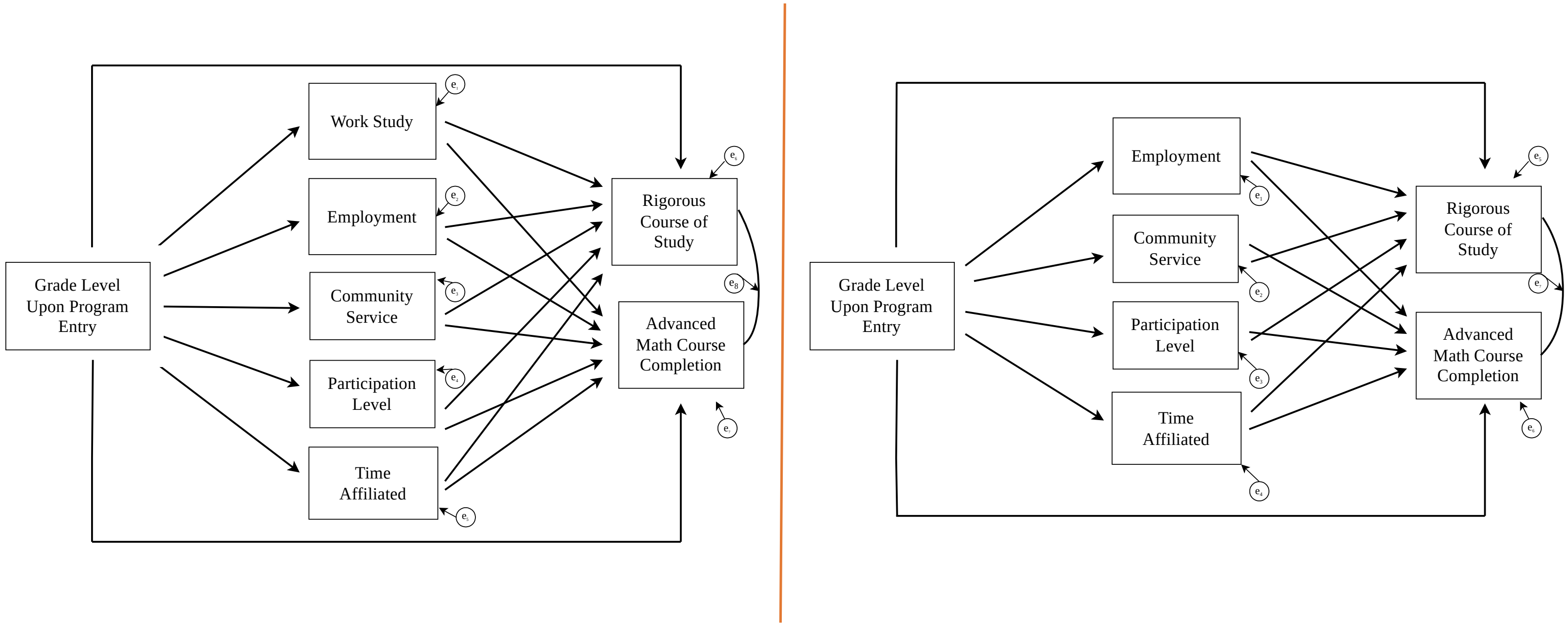
4. Test Causal Mechanisms to Possibly Explain Outcomes

Before delving into testing the causal mechanism of path analysis proper, one pauses to take the time to assess the overall fit of the model to the data. In simple linear regression, the fit is generally reported through the coefficient of determination (R^2) to provide a sense of how well the model fits the data. When investigating a number of predictor variables within the same structural equation modeling (SEM) framework via path analysis, however, one arrives at this sense of model fitness by observing how the model fairs against a model-identification filter and, subsequently, to assess in a more robust way the degree to which the model fits the data. This strategy allows the researcher to use a number of model-fit indices to determine how well the model actually fits the data and proceed to employ path analysis procedures to make inferences regarding correlation and, possibly, causation. In this unique instance, before exploring model fitness, one considers a slightly adjusted model from the one proposed in the previous chapter.

Model Modification. Initially, the proposed UBMS model focused on six predictor variables and two separate output variables. When proposed, little was known of each variable with respect to data variability and utility. Upon inspection of the data, the predictor variable which provides information on whether students participated in internship or apprenticeship experiences (i.e., Work Study) was determined to be unusable. Not enough variability existed in the data for that variable; only one student from the sample of interest participated in such an experience, making it difficult to assert any potential implications onto either of the two dependent variables. As such, removing that specific predictor variable was the advisable route to follow. Figure 16 unveils the updated model to be examined.

Model Identification. In order to ensure that the model to be explored is appropriate and sensible, one first assesses its fitness to the data. To do this, one performs a simple comparison of parameters latent in the model. One considers Figure 17, an adaptation of the new model, illustrating it from the perspective of the parameters linked to the model. Specifically, the model has five predictors and two outcomes reflecting heightened STEM interest. Outcomes are whether students attained a rigorous course of study and whether they completed advanced math courses.

Preliminarily, the number of unknown parameters loosely corresponds to the number of unique paths that exist between exogenous and endogenous variables. As indicated in Figure 17, there are 14 such paths. Six parameters that are typically estimated



Initially Proposed Model

Updated Model

Figure 16. *An Updated Upward Bound Math Science Path Analysis Model*

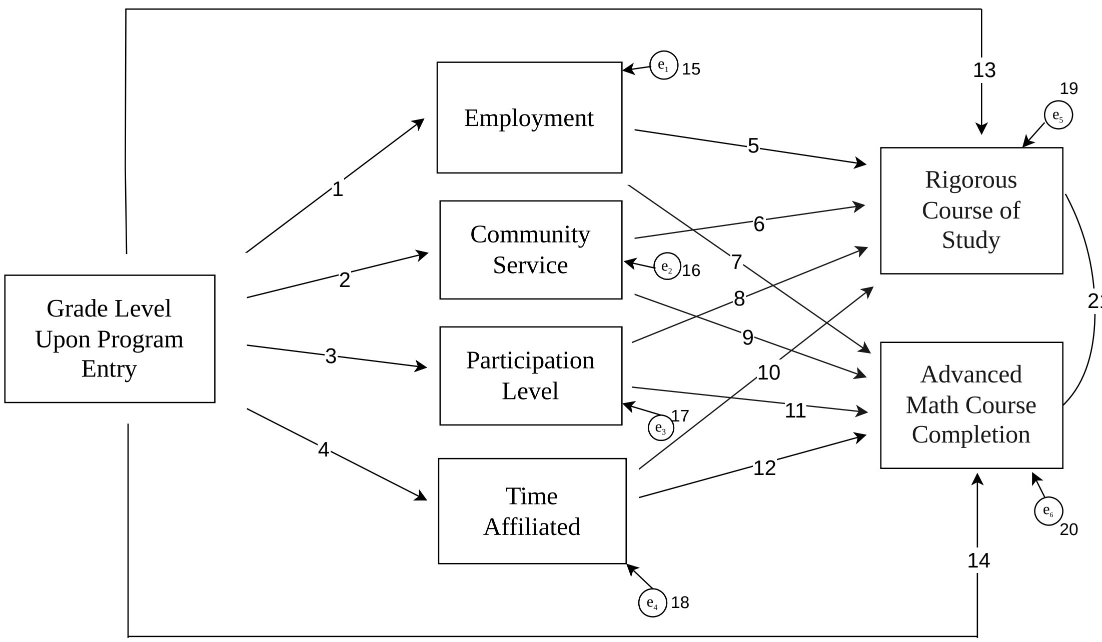


Figure 17. *Visualizing Known and Unknown Parameters*

as part of a path analysis are the residual error terms, indexed by e_i. They generally are affixed to each endogenous variable within the model as a contributing source of variance. The last connection involves the two output variables, which have no presumed causal connection in this case. No arrow joins them since neither is claimed to predict the other. This particular relationship exploits the last residual error term accounted for in the model. Together, this leads to a total of 21 unknown or free parameters, observable in Figure 17.

The number of known parameters is compared to the unknown ones. In this instance, the number of known parameters or unique sources of information in the model is given by $\frac{p(p+1)}{2}$, where p corresponds to the number of manifest variables included in the model. Again, the model contains seven variables, illustrated by rectangles. Of these variables, one—grade level upon program entry—is exogenous and the other six are endogenous, those for which one may monitor their alleged specific cause. The number of known parameters, then, is $\frac{\mathbf{7(7+1)}}{\mathbf{2}}$ or 28.

In traditional SEM theory, initial determination of a model's fitness is measured by the comparison of the unknown parameters to known ones. In this case, the 28 known parameters exceed the 21 unknown ones. Because the known parameters exceed those that are unknown, the model is characterized as overidentified, which is a good thing in this context because it allows one to test for model fitness (Altikriti & Anderson, 2021). If both parameters were equal or if the number of unknown parameters exceeded known ones, continuing on to test model fitness would be impossible. Satisfying this criterion early on prevents the researcher from wasting valuable subsequent time assessing whether the model is adequate from a superficially structural perspective.

Model Fit Indices. A second layer of model scrutiny involves the testing of the model through model fit indices. Essentially, this stage of analysis investigates how well or poorly the proposed model fits the data by offering relative assurance that analysis which is to follow is lodged in a statistically vetted system or process (Shi et al., 2019). For the UBMS model presented in Figure 17, five commonly used model-fit measures are reported: Chi-square test (χ^2), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). Such model-fit indices are well known for investigating path models in math and science education when the goal is to examine interaction between motivational, cognitive, and affective variables (Kirbulut, 2014).

Each test has its own specialty in evaluating certain aspects of the model that make it “good” or “bad” to use in the analysis. The RMSEA technique, for example, gauges the balance in the number of predictor and output variables used in the model as well as the number of possible paths (i.e., directional arrows) proposed. It essentially penalizes any projected model that attempts to use extraneous variables with as many paths or arrows between them as possible, hoping to “throw spaghetti to the statistical wall” to get something to “stick.” Hence, accuracy through parsimony is rewarded (Taasoobshirazi & Wang, 2016). Table 9 summarizes the model fit of the proposed UBMS path model in light of these five indices and determines whether the model is reasonable to use; thresholds for indices are well-known standards across the statistical literature (e.g., Perera et al., 2020; Chou et al., 2022). The table is supported by the results in Appendix B.

Although no specific standard exists concerning how many of the fit-indices tests that the model should pass before being considered as a reasonable fit to the data, researchers are advised to use them in combination rather than singly in order to loosely triangulate the model’s efficacy (Cheung & Rensvold, 2001). If the projected model fails to meet any of the thresholds, however, one should hesitate to interpret any of the resulting path coefficients. Generally, more thresholds that are met tend to suggest better statistical reliability in the interpretation of these coefficients. Table 9 shows the five conventional threshold index values and index values for the projected UBMS model; it further summarizes which indices support or do not support the use of the model. Results reveal that the model is supported by three of the five indices. Making subsequent analysis of path results for the model, one could argue, is a worthwhile endeavor.

Table 9

Proposed Path Analysis Model and the Five Model Fit Indices

Index Reference	Chi Square Test	Comparative Fit Index	Tucker-Lewis Index	Root Mean Square Error of Approximation	Standard Root Mean Square Residual
Index Thresholds Indicating Good Model Fit	$p \geq .05$	$CFI \geq .9$	$TLI \geq .95$	$RMSEA \leq .08$	$SRMR \leq .08$
Index Value of Proposed Model	$p = .12$	$CFI = .91$	$TLI = .69$	$RMSEA = .10$	$SRMR = .07$
Proposed Model Supported with Index?	✓	✓	✗	✗	✓

Addressing the Normality Assumption of Residuals. One major assumption in using path analysis as a technique to investigate models is that of the normality of residuals. Residuals in a model, often referred to as error terms, provide an overall sense of values in the proposed model compared to expected values. Assuring their normality goes far into assuring a certain level of reliability in results and inferences that one is able to make regarding the model and its fit to the data (Lee et al., 2020). One systemic way of handling a possible violation of this assumption is by structuring the study's analysis based on resampling the simple dataset to create several simulated samples; this process, called bootstrapping, indirectly obtains the required normality of residuals by landing on a sampling distribution whose estimates and confidence intervals become useful in the interpretation of the results (MacKinnon et al., 2004). In this study, bootstrap resampling was employed to test the significance of direct and mediated effects in the models. To ensure accuracy, the number of repetitions was set conservatively at 5,000.

Path Analysis Results. Results for the model relay insightful information on the outcome variables, both of which signify students' STEM interest at the outset of their postsecondary educational pursuit. These variables assess to what extent students were likely to take on a rigorous course of study and complete advanced math courses beyond algebra 1 by graduation. Both variables are defined in the Measures section in chapter 3. As customary when analyzing path results, one should pay close attention to significant direct effects between predictor variables and outcome variables. Table 10 displays such results between the two variable types, as well as associated z values, p values, and standardized path estimates. In our analysis, the typical threshold for p values is the typical 0.05, which translates into a critical value for z of ±1.96.

In addition to determining if significant direct effects prevail, one further considers whether any prominent indirect effects between variables exist. Mediation, in path analysis theory, refers to such an indirect effect of an independent variable onto a dependent variable that traverses through another intervening variable (Sarstedt et al., 2020). If a significant direct predictive association already exists between a predictor variable and an outcome variable, then the association is dubbed as a significant partially mediated relationship among the trio (Servidio, 2021). Otherwise, the mediated relationship is a significant fully mediated one (Hoi, 2020). Table 11 provides insight regarding mediation between all possible combinations in the path analysis.

Table 10

Path Results for UBMS Model: Direct Effects

Predictor Variable	Outcome Variable	*z* Value	*p* Value	Standardized Path Estimate
Grade Level Upon Program Entry	Completion of Advanced Math Courses	.29	.77	.05
Employment	Completion of Advanced Math Courses	1.61	.11	.18
Community Service	Completion of Advanced Math Courses	–3.10	.00	–.33
Level of Participation in the Program	Completion of Advanced Math Courses	.10	.92	.01
Time Affiliated with the Program	Completion of Advanced Math Courses	.72	.47	.11
Grade Level Upon Program Entry	Employment	–.04	.97	–.00
Grade Level Upon Program Entry	Community Service	–1.24	.22	–.12
Grade Level Upon Program Entry	Level of Participation in the Program	1.09	.28	.10
Grade Level Upon Program Entry	Time Affiliated with Program	–4.14	.00	–.49
Grade Level Upon Program Entry	Obtainment of a Rigorous Course of Study	2.91	.00	.34
Employment	Obtainment of a Rigorous Course of Study	.58	.56	.06
Community Service	Obtainment of a Rigorous Course of Study	–1.15	.25	–.14
Level of Participation in the Program	Obtainment of a Rigorous Course of Study	1.45	.15	.27
Time Affiliated with the Program	Obtainment of a Rigorous Course of Study	1.30	.20	–.17
Obtainment of a Rigorous Course of Study	Completion of Advanced Math Courses	.68	.50	.09

Table 11

Path Results for UBMS Model: Indirect Effects

Predictor Variable	Proposed Mediating Variable	Outcome Variable	Indirect Effect	Confidence Interval		*p* Value
				Lower Bound	Upper Bound	
Grade Level Upon Program Entry	Community Service	Obtainment of a Rigorous Course of Study	.02*	−.01	.05	.40
Grade Level Upon Program Entry	Employment	Obtainment of a Rigorous Course of Study	−.00	−.01	.02	.98
Grade Level Upon Program Entry	Level of Participation in the Program	Obtainment of a Rigorous Course of Study	.03	−.01	.11	.55
Grade Level Upon Program Entry	Time Affiliated with the Program	Obtainment of a Rigorous Course of Study	.08	−.04	.15	.26
Grade Level Upon Program Entry	Employment	Completion of Advanced Math Courses	−.00	−.03	.05	.97
Grade Level Upon Program Entry	Community Service	Completion of Advanced Math Courses	.04	−.01	.10	.24
Grade Level Upon Program Entry	Level of Participation in the Program	Completion of Advanced Math Courses	.00	−.02	.05	.95
Grade Level Upon Program Entry	Time Affiliated with the Program	Completion of Advanced Math Courses	−.05	−.15	.12	.50

**Note: .02 = −.12 × −.14 (See Fig. 18: The indirect effect is the product of the 2 effects along relevant paths.)*

Hypothesis testing comes into play when interpreting these standardized path estimates (i.e., coefficients). For direct effects, the decision criteria are based on *p*-values. If $p < 0.05$, results suggest that there is a significant positive or negative predictive (and possibly causal) effect between connected variables. For indirect effects, decision criteria are dependent upon bootstrapped-based confidence intervals. If zero is not contained within reported upper and lower bounds, a significant predictive (and possibly causal) effect exists between connected variables. Table 11 shows that zero is, in fact, contained within the confidence intervals for all cases of possible mediation; hence, no intervening variable serves as a significant mediator between any of the predictor-outcome relationships.

Figure 18 offers a more visual representation of Tables 10 and 11, featuring the model with its appropriate coefficients labeled on each path. Black-colored connections represent paths which display a significant relationship between adjoining variables. Light gray paths indicate insignificant paths between variables. Values along paths are size effects; they are standardized path coefficients, which convey the degree to which the predictor variable correlates to the outcome variable. The larger the value—positive or negative—the more significant the correlation. Subsequent analyses are beholden to the black, significant paths as opposed to the gray ones. Path analysis results, in fact, offer a more intricate perspective from which to derive predictor-outcome relationships.

And Table 12 displays the correlation matrix for the variables at play. Considered altogether, path analysis results show the details behind this traditional matrix, which gives a bird's eye view of associations between both predictor and outcome variables. Data in both the path analysis and correlation matrix provide identical information, just at varying intensity levels. Values in black in the matrix correspond to routes in black—significant routes—along the path analysis. One should not expect an exact replication in values between the two representations, however, as some of the coefficient values in the path analysis are absorbed by the error terms.

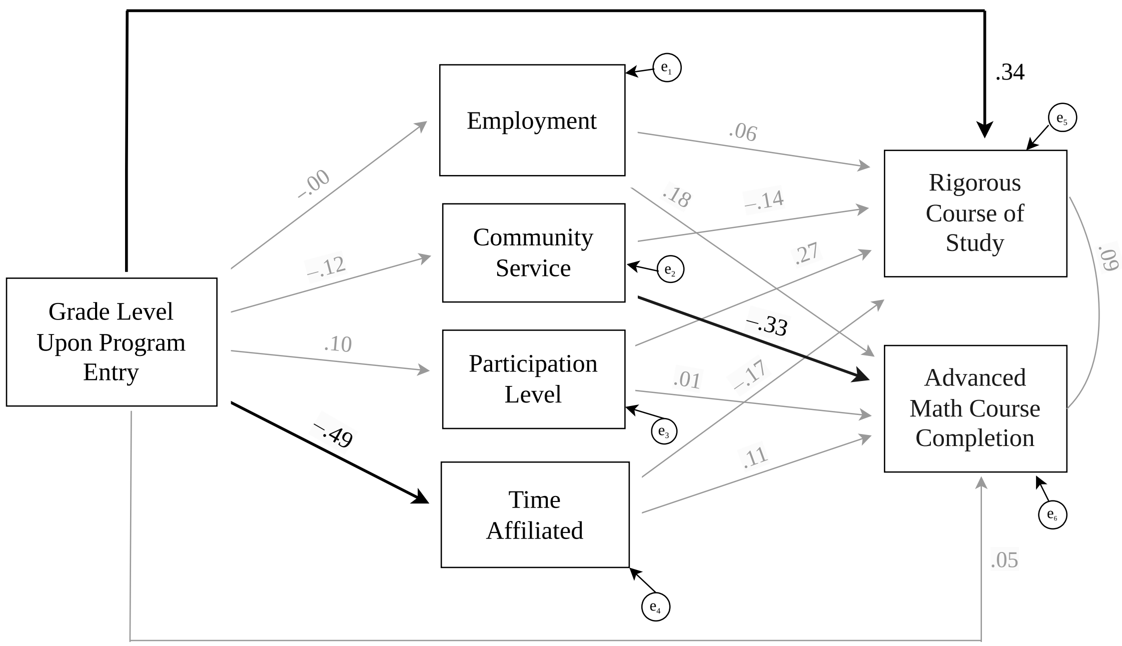


Figure 18. *Model with Standardized Path Coefficients*

Employment as Outcome. One of the benefits of path analysis is that results allow for the interpretation of variables as both predictors and outcomes simultaneously, depending on where they are in the model. With respect to employment as the output variable, model results support that there is an insignificant effect between the grade level when UBMS students begin the program and whether they take on a job while in the program (b = –.00, p = .97). Thus, the grade level at which students enter the program does not have a predictive effect on whether students decide to become employed while enrolled in the program.

Table 12

Correlation Matrix for UBMS Study

	Community Service	Time Affiliated with the Program	Completion of Advanced Math Courses	Employment	Level of Participation in the Program	Grade Level Upon Program Entry	Obtainment of a Rigorous Course of Study
Community Service	–	.27	−.32	−.12	.08	−.10	−.25
Time Affiliated with the Program		–	.10	.07	.03	−.43	−.38
Completion of Advanced Math Courses			–	.22	−.08	−.10	.15
Employment				–	−.12	.01	.04
Level of Participation in the Program					–	.07	.27
Grade Level Upon Program Entry						–	.44
Obtainment of a Rigorous Course of Study							–

Community Service as Outcome. One considers community service as an outcome variable. Results support that no significant predictive effect exists between when students begin the program and if they participate in any kind of community service once they join the program ($b = -.12, p = .22$). Hence, the grade level at which students enter the UBMS program has no predictive effect on whether they will be involved in any type of community service once in the program.

Participation Level as Outcome. As an outcome variable, the level of students' participation in the program is not significantly predicted by when students enter the program ($b = .10, p = .28$). Nothing in the model supports the fact that students' grade level upon entry into the program has any significant predictive effect on program dosage or the level of their participation (i.e., whether students participate during summers only or during the academic year and summers or any other combination of their participation scope).

Length of Time with Program as Outcome. Results show that the grade level in which students enter the UBMS program has a significant negative predictive effect on the length of time they remain affiliated with the program ($b = -.49, p = .00$). This result is not a particularly surprising one. It suggests that the later grade that a student enters the UBMS program, the less time they are affiliated with the program. Indirectly, it supports the notion that those who enter the program earlier in their high school career tend to remain in it for a considerable amount of time, mostly through graduation; essentially, the evidence does not support any trends signifying early student exits from the program.

Rigorous Course of Study. One recalls that one of the two major output variables anchoring the study is whether or not students obtained a rigorous course of study by the time they finished high school. According to Figure 17, the prediction equation for whether or not students obtain a rigorous course of study is as follows using standardized scores:

$$Rigor = .34GrdEntry + .06Employ - .14Comm + .27Part - .17Affil + e_{Rig}$$

Only one of the five variables has a significant direct predictive effect on whether students obtain a rigorous course of study. The grade level at which students entered the UBMS program has this significant positive predictive effect on whether students obtained a rigorous course of study ($b = .34$, $p = .00$). Thus, the later students entered the program, the more likely they seemed to have achieved such a course of study. Said another way, the earlier they began the program, the less likely they seemed to have achieved said course of study. The other four variables, though related to students' having a rigorous course of study, were not significant predictors for it. This finding may provide somewhat counterintuitive to what one might expect. Upon closer inspection, however, this may not necessarily be a cause for alarm.

Figure 19 provides a look at the actual data contributing to the finding. One observes that only five students joined the program in the eleventh grade. It is the case that all of them ended with a rigorous course of study by the time they graduated. It is a strong chance that they may have even achieved such a course of study by the time they entered, although data does not reveal when students achieved that benchmark. There are many more freshmen who joined the program than those who joined as juniors, increasing the chance that many of them would not obtain a rigorous study course. One notices that 19 freshmen successfully achieved this feat, along with 10 of them who did not. Hence, the proportion of those reflecting those who did and did not is roughly 66%.

And only one student out of the tenth-grade contingency did not achieve such a course of study.

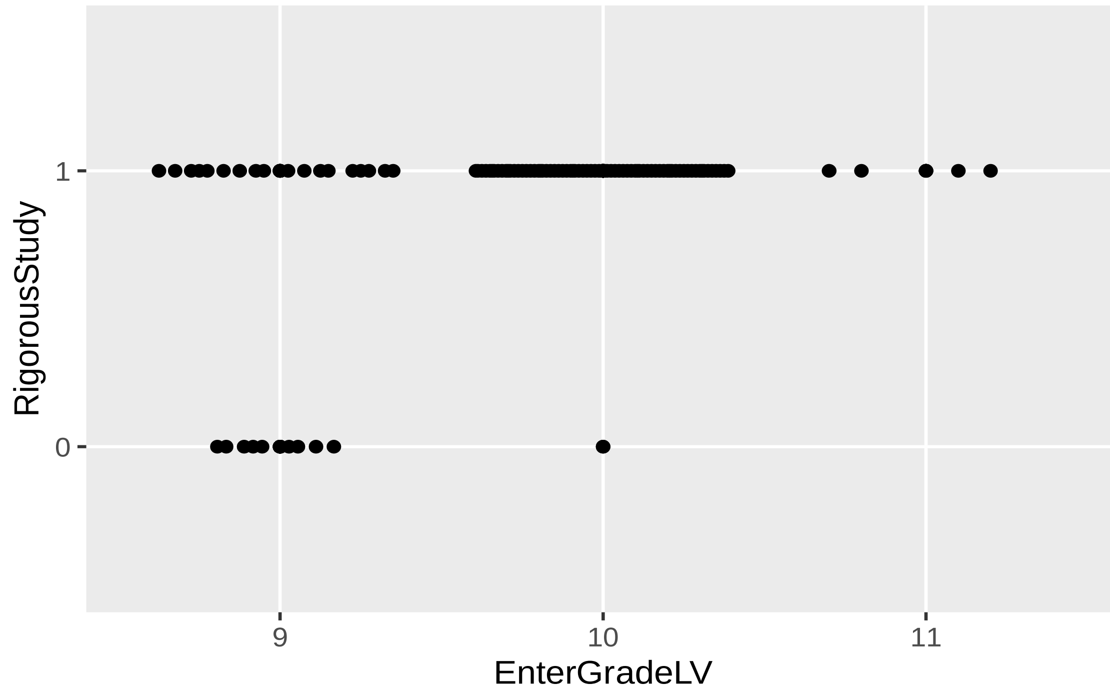


Figure 19. *Beeswarm Plot: Students' Entering Grade Level and Their Attainment of a Rigorous Course of Study*

The reported standard coefficient by itself does not elucidate the relationship between grades; it only establishes grounds for exploring on a deeper level. For this relationship, the phenomenon among the eleventh graders with the low student pool and perfect rate of attainment might produce more angst than it should when one analyzes it in light of proportional comparisons. Attacking the analysis in this way keeps comparisons on a similar scale of analysis; however, the analysis is oblivious to the base count per grade level and how it factors into findings. The program does indeed seem to have a positive impact on students who enter the program early on with respect to obtaining a rigorous course of study. They just run the risk of offering low proportion rates of success by the time graduation comes if they begin with many more students at this level in the program than in others.

One considers a few hypotheses regarding this observed trend. As students left the program, those who replaced them could have been eleventh graders who already had rigorous courses as part of their academic pedigree upon entry. Not an illogical perspective, admitting students who were close to fulfilling such benchmarks keeps the program on track for reaching its mission. Another possible hypothesis for the trend is that students may have received more counseling and guidance during their ninth-grade year prior to entering the UBMS program. Hence, by the time they entered the program in the tenth grade, they may be more academically focused and mentally prepared to tackle courses more rigorous in nature. To have a huge mass of students who began the program during their sophomore year and only one not attaining a rigorous course of study suggests that their affiliation with the program is, at the very least, not hurting their choice of course load. Relatedly, ninth graders beginning the program may not have had the same amount of academic counseling as others or received it and paid it little to no attention. As a result, a larger percentage of them fell short of attaining a course study of rigor during their high school years in comparison of those starting in later grades.

Advanced Math Course Completion. Similar to the decision to obtain a rigorous course of study, students' choice to complete advanced math courses is also significantly predicted by only one of the four possible variables in the model. The prediction equation for whether or not students took advanced math courses beyond algebra 1 is as follows using standardized path coefficients:

$$Adv = .05GrdEntry + .18Employ - .33Comm + .01Part + .11Affil + e_{Adv}$$

Results reveal that students' participation in community service has a significant negative predictive effect on whether students completed advanced math courses by the time they finished high school ($b = -.33, p = .002$). That is, as the number of students who participated in community service activities increased, the number of them who completed advanced math courses tended to decrease. None of the other four proposed predictive variables had a significant effect—positive or negative—concerning whether students decided to pursue advanced math courses in high school.

Students' increased involvement in the community service aspect of the program predicted a reduced number of students who completed advanced math courses. Said differently, students who failed to participate in community activities were predicted to demonstrate an increase in the likelihood that they would complete advanced math courses. These empirical findings seem to run counter to modern research concerning postsecondary preparedness, which tends to tout the presence of community service as one of several key measures of college and career readiness (Kurlaender et al., 2019). A closer look at the data shows a few interesting occurrences that may shed light on the results; observing community service data by year reveals an interesting development, as seen in Figure 20.

The lower left panel conveys the number of UBMS students who did not participate in community service activities. The years 2018 and 2019 represent academic years 2018–2019 and 2019–2020, respectively. It is conceivable during year 2019 (or 2019–2020) that every student did not participate in community service activities because they were not offered. Not one student participated in such service, as evidenced by the upper right panel of Figure 20, as no bar appears for the same year. This time period coincides with COVID-19, during which time UBMS leadership terminated all community service engagement involving students; in-person gatherings were on pause and programs like UBMS had to place safety over service. If no services were offered, students could not participate, leaving more than enough time to focus on studies. Program leadership may have decided to note their non-participation as a hard “no” as opposed to being dubbed as “non-applicable.”

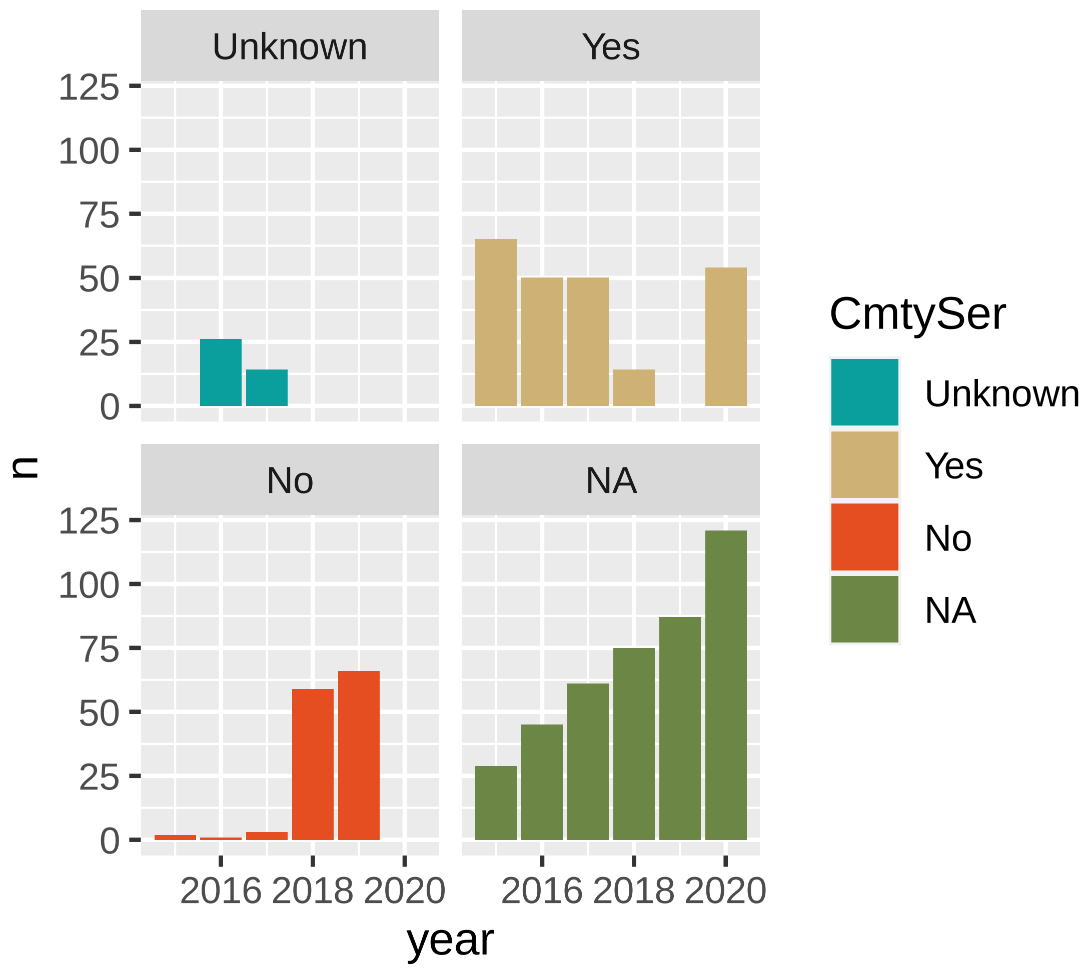


Figure 20. *Community Service by Participation Status and Year*

For 2018 (i.e., 2018–2019), no apparent reason seems to explain why such a large number of students did not participate in community service. The pandemic had not yet arrived in the U.S. These seemingly anomalous findings—displaying much higher numbers of students not participating in community service than just the year before—cast slight doubt on values recorded for that year for that variable. The astute researcher raises a brow if witnessing abrupt changes in trends when no obvious external effect occurs—like COVID-19. Even so, no trend tends to support or foreshadow this data quirk. This is particularly notable since fulfilling community service is mandatory and offers a stipend. For so many students to willingly buck against the program's mandates in this regard and even forfeit their monetary reward is a hard notion to digest. One could surmise that, because data do not appear to follow any trend before or afterward, faulty human data entry even remains a possibility. This pair of seeming date anomalies are indeed features impacting analysis concerning students' community service and its association with whether or not students completed advanced math courses. One should proceed with caution when attempting to declare that, in this unique case, students' participation in community service portends their mediocre pursuit to complete advanced math courses.

5. Interpret Pattern of Findings to Facilitate Generalization and Knowledge Transfer

In the overall scheme of program evaluation for the UBMS program at Temple, the model offers a few key findings with respect to students' attainment of a rigorous course of study and completion of advanced math courses. Students in the program appeared less likely to obtain a rigorous course of study if they entered at an early grade. Moreover, results only tend to suggest that students in the program appeared less likely to take advanced courses beyond algebra 1 if they participated in program-sponsored community service activities. As discussed, however, these findings come with caveats based on observations specific to data interpretation for those variables. Table 13 summarizes all direct and indirect significant relationships in the tested model.

Table 13

Direct Significant Associations Between Predictors and Outcomes

Predictor	Outcome
Grade Level Upon Program Entry	Time Affiliated with the Program
Grade Level Upon Program Entry	Obtainment of a Rigorous Course of Study
Community Service	Completion of Advanced Math Courses

6. Identify Formative Uses of Findings for Program Improvement

Though causal models in general do not automatically assert that significant model findings provide evidence of causality between variables, CPE theory lays out several cumulative criteria—from least to greatest—with respect to identifying possible evidence of causal inference. Findings for the UBMS program at Temple provide the basis for exploring most of these criteria as one considers an assessment of causality. Such criteria include temporality of program exposure, strength of association, gradient effect, specificity, consistency, and coherence (Susser, 1973; Anderson et al., 1980; Reynolds, 1998). Figure 21 presents a measuring tool, the CPE "Cause-ometer," (coined by the author), which provides a visual rendering of these causal criteria. After considering UBMS findings with respect to thresholds, one determines where the model approximately fits on the tool's causal spectrum.

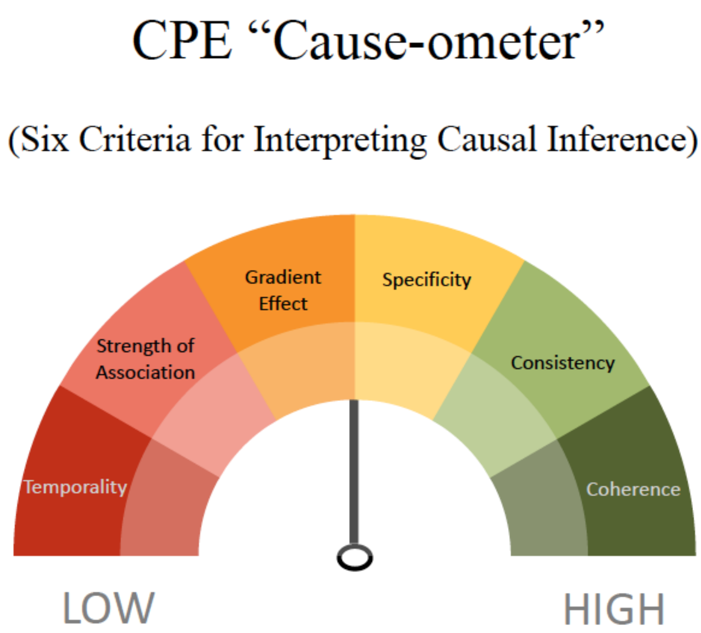


Figure 21. *The Confirmatory Program Evaluation "Cause-ometer"*

Note: Design by PresentationGo

Temporality of Program Exposure. The bar for this level of alleged causality is low. The only requirement to fulfill at this level is that the causal variables must happen prior to the outcome variables (Reynolds, 1998). While this may be obvious in most studies, it is not always the case, depending on which analysis technique is explored. The UBMS path analysis model used herein meets this standard. The model is indeed recursive; in other words, all arrows flow in one direction with no feedback loops. All predictor variables precede outcome variables with respect to time.

Strength of Association. Next, the association between student participation and program outcomes is key to promoting causal claims within a model, according to CPE theory. An effect size of one or two standard deviations tends to describe a situation in which the program had a meaningful effect on participants (Reynolds, 1998); extremely low *p*-values (i.e., less than .001) tend to keep stride with this deviation range. As discussed, three of the 14 predictive associations in the UBMS model are significant in that they exceed this two-standard-deviation threshold (see Table 10); this represents a mild 24% of the associations. The two pairs of variables that appear to have the strongest plausible causal connections are: (1) the predictive path linking grade upon program entry and students' affiliation time with the program ($p = 0.000$) and (2) the one linking proportion of students doing community service and their completion of advanced math courses ($p = .002$). Hence, these were the most relevant to the theory of the UBMS program. Overall, the strength of association is relatively weak.

Gradient Effect. The gradient effect refers to the relationship that exists between program exposure and the program outcome; a stronger causal inference is likely if the outcome positively improves as "an increasing function of the amount and duration of program participation" (Reynolds, 1998, p. 208). In the UBMS data, the variable closely related to this describes the students' participation level throughout the program. Students participated in the program at various "doses." In this study, students' attainment of a rigorous course of study does indeed improve as an increasing function of their participation level ($b = .27$) but not significantly ($p = .15$), suggesting that a strong causal inference is not likely. Likewise, students' completion of advanced math courses does also improve as an increasing function of their participation level ($b = .01$) but not significantly ($p = .92$). One observes, then, that no gradient effect exists in the UBMS model.

Specificity, Consistency, Coherence. In CPE theory, specificity of association refers to situations in which outcomes are limited to certain outcome conditions; in educational circles, findings that hold with the program theory but do not for other theories tend to strengthen causality (Reynolds, 1998). Consistency references the ability of program effects to remain intact across subpopulations, times, places, and for similar program theories; the more consistent the findings are with respect to effects, the more likely the effects are real and causal in nature (Reynolds, 1998). The highest threshold to obtain on the causal continuum, according to CPE theory, is that of coherence, the ultimate criterion assessing as a whole the previous five causal conditions discussed earlier; considering the program theory, the degree to which findings merge with evidence about temporality, size, gradient, specificity, and consistency determines how coherence and, ultimately, causation is fortified (Reynolds, 1998). Often, evidence supporting coherence for program effectiveness spans over several studies or through meta-analysis.

The findings in the UBMS study support neither specificity, consistency, nor coherence. No other program theories are available against which the study's program theory and results can be compared. In this regard, testing for specificity is not practical herein. Second, results obtained from path analysis were based on a reduced sample or those who were assigned a bona fide PSE cohort, a reduction from the original sample in the initial study. To obtain an even smaller race-, gender-, or otherwise-based subpopulation from this reduced one would sacrifice a sense of reliability, increasing the chance of a Type 2 error. Last, one may wish to test the proposed model with different UBMS programs in various locations; at the core, students would be similar to UBMS students at Temple in that they must be FGLI students; however, testing the model for UBMS students whose demographics and ethnographies vary from those in this study would provide more robust results.

Where Temple's UBMS Program Fits. Using the created "cause-ometer," one can loosely assess where Temple's UBMS program fits within the six defined levels on CPE's causal continuum. The model being used to assess the program in question crosses the first threshold and a small portion of the second one. Though the UBMS model's placement on the "cause-ometer" is not precise, it conveys a general idea of how the model measures up to asserting claims of causality with respect to the two outcomes, according to the CPE theory. Figure 22 highlights this causal stance.

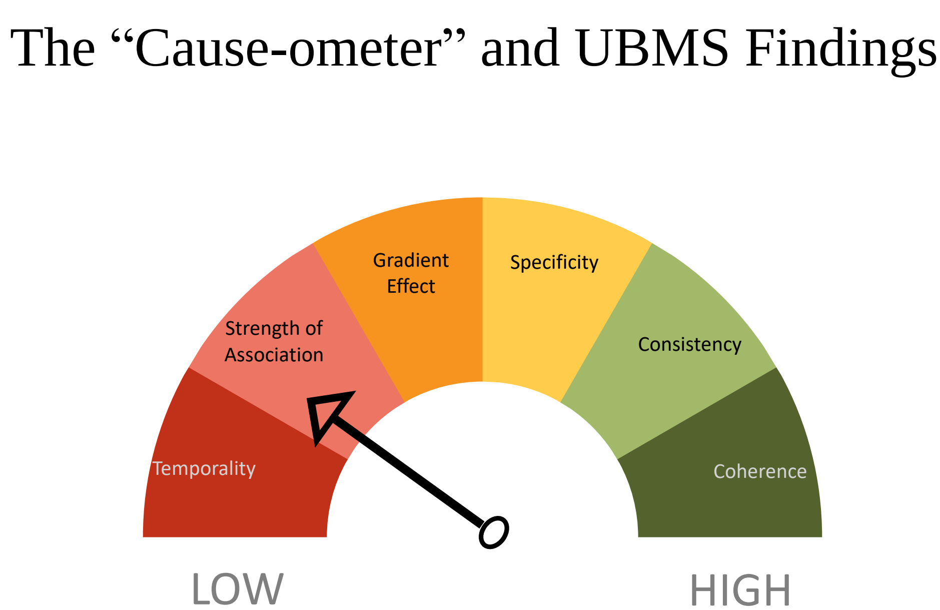


Figure 22. *The "Cause-ometer" and Upward Bound Math and Science Findings*

Note: Design by PresentationGo

CHAPTER 5

LIMITATIONS, RECOMMENDATIONS, AND IMPLICATIONS

Evaluation of programs can provide valuable information regarding how effective or ineffective they are at fulfilling their missions. Assessment of these programs is crucial in order to ensure timely and adequate services to student clients; in some circles, appropriate scrutiny of program operation and associated results can determine whether or not funding is maintained or renewed. This modest investigation of Temple's UBMS program hopes to provide some cursory internal glance at relatively current program operation and offer support to strengthen its effectiveness. Some brief discussion is dedicated to limitations associated with the study. Next, several recommendations are offered, which program leadership might find useful. Finally, several implications are addressed as related to policy and other realities within educational spheres. Discussion surrounding recommendations and implications in this chapter should be understood solely as being derived from the researcher's experience and perspective, not from inference that is suggested by any of the data used in the study.

Limitations

The Limited Reach of CPE

In a broad sense, the main limitation of the study is simply the limitation of trying to draw definitive conclusions about an important program using only one evaluation scheme. While CPE outlines sound theory for evaluating programs, it is indeed only one of several. It is not meant to serve as the sole lens through which the program's effect should be analyzed. Its theory merely complements other analytical approaches to evaluate programs and does not replace them. It should be used in tandem with other informed theories to uphold or refute overall alleged causal claims. It has carved its own niche in theory-driven research regarding program evaluation, but the borders of its footprint are indeed finite. Corroboration of UBMS findings herein should be supported or debunked using long-standing, alternative evaluative schemes. Even when findings pass the highest level of scrutiny in CPE's evaluative protocol (i.e., coherence), no decisive statement can be made about causal inference; one may only assert that causal conjecture is highly strengthened (Reynolds, 1998). Even so, reasonable recommendations may be offered to program stakeholders, and sensible policy may be crafted or changed, depending on the strength of plausible causation.

Geo-cultural Realities

The model of analysis presented in the third research question was designed specifically for the overall student profile in Temple's UBMS program. All of the students in the UBMS program at Temple reside in the city of Philadelphia. They harbor some degree of cultural uniformity as well as regional similarity. These traits hinder the ability to generalize results for populations outside of the ones in this study. Certain variables included in the model for one study may need to be altered for another study, which supports how flexible the analytical technique is. Statisticians have to be keenly aware of the SIP's environment and, accordingly, be astute in crafting the CPE-based model for it. Programs that serve students having different demographical profiles may require updated, tailor-made models to be analyzed. Hence, results suggested herein may only be applicable to the specific UBMS program at Temple or, at most, to UBMS programs whose students share similar geo-cultural reference points. Main reference points include, but are not limited to, populations whose students are:

- members of the FGLI community;
- mostly Black;
- mostly female;
- English speaking;
- enrolled in high schools whose vast student majority are free-lunch eligible;
- moderately to highly interested in math- or science-based careers.

Lack of Data Specificity for Some Variables

Further, it is not detectable when students attained rigorous courses of study or completed advanced math courses in the program. It is conceivable that students who entered the UBMS program as juniors could have already achieved either benchmarks or both. This lack of clarity concerning when such a course of study was secured or advanced math courses were obtained in relation to when students entered the program could eat away at any possible causal claims that the program would hope to assert between associated variables.

Missing Data

The third research question depends on data for those who have been assigned a PSE cohort. One may recall that 110 students comprise this more refined subgroup of students. As such, one expects that most of the data concerning this postsecondary-bound sample of students would be available for the path analysis phase of the study. For many of these students, however, a lot of the data is missing with respect to their community service, participation level, and employment. Some of the missing data overlaps with the onset of COVID-19 onto the world’s stage in which program services halted for much of 2020. Many of the intervention efforts went virtual. So, this phenomenon could have affected interpretation of the results significantly. However, missing data were not solely bound to COVID dates.

Though the path analysis procedure retains as much of the data as it can through the Full Information Maximum Likelihood (FIML) methodology, challenges endure when a huge chunk of data remains sparse. In this study, findings reveal that only 65 of the 110 students' information is used in obtaining the standardized coefficients that lead to significant or insignificant paths between predictor and outcome variables (Tables 10 and 11). Kline (1998) suggests that an ample sample size for path analysis should be at least 10 times the size of the number of parameters in path analysis. With seven parameters in the UBMS path analysis model and 65 used data points, the sample falls just short of the 70 students recommended minimum for this instance. This should not greatly affect standard estimates arrived at in the study since the sample size is so close. One wonders, though, whether any other significant paths between predictors and outcomes would arise or if any found significant ones would be rendered insignificant if data were available for the remaining collection of students.

Initially, the goal in this study was to analyze predictors and their relation to specified outcomes using all of the data and then to do the same with logical subsamples within the population. Looking at predictor-outcome relationships involving these smaller group clusters would have allowed analysis at a more granular level and perhaps pinpointed any observations not detectable when considering the whole of the data. Missing data in the study, however, hamstrung any efforts in the study to investigate these subsamples. Analyzing these subpopulations related to ethnicities or gender or any other demographic gathering depended on having enough data available for those same clusters. Moving forward to obtain statistical estimates with the subsamples as is would have yielded unreliable and biased results because of their low numbers. Having ample data in studies of these types is crucial, becoming the driving force behind being able to offer solid inferences.

Missing Variables

Out of the control of Temple's UBMS administration is the lack of data collection for certain variables, which could offer further insight on the effectiveness of the program. Part of the program's stated mission involves providing students with tutoring, counseling, and mentoring services. Yet, APRs require none of the program leadership at any of the host campuses to collect and store data related to any of these three aspects of the program. This information could provide an invaluable perspective on how these services might impact student STEM interest.

If data for these variables were collected in some quantitative form, they would become analyzable within the context of a path analysis study such as the one conducted by this researcher. It is the national program leadership's sin of omission; local program leadership only reports data that is required on APRs designed by grant funders. If such data were at the researcher's disposal, some statement offerings would be available regarding possible causal linkages between tutoring, counseling, and mentoring as they relate to students' likelihood in obtaining a rigorous course of study and in completing advanced math courses beyond algebra 1.

Recommendations

Continue Reaching High Numbers Regarding Postsecondary Pursuit

Data reveal that Temple's UBMS students pursue some type of postsecondary pursuit at a rate significantly higher than their UB counterparts. In fact, data show that close to 95% of UBMS students in the study pursued postsecondary education. Though there may be challenges to contend with regarding various aspects of the program, leadership should feel some sense of accomplishment because of this fact. The success strategy that the program has relied on, despite the number of administrative changes it has undergone over the past decade, appears to have still delivered on the ultimate aim of pushing the students to continue with their education beyond high school and, perhaps, with their entry into the STEM workforce. There is no evidence that supports that students' involvement with the program is the primary reason they go on pursue postsecondary education, but neither is there any evidence supporting that their involvement with the program has hindered their pursuit. Though some attrition away from the STEM field may be unavoidable after high school years, the program is generally doing its part in preparing students to reach the first phase of their postsecondary STEM journey.

Engage Target Schools More

The program planned to render services to a number of target schools in the Philadelphia area over the past few cycles. None of the data was available for these target schools, however, when the researcher prepared to compare them to non-target schools. Such comparisons would have been invaluable when viewing the overall picture of the program's effectiveness. Do students from target schools—which often lack many of the needful resources for adequate support—eventually reach similar academic levels as those from non-target schools? Are there significant differences between both groups concerning postsecondary realities? The program would serve itself well to collect and store data regarding these target schools in a more conspicuous way for researchers to use.

Regarding data organization specifically, NCES school identification numbers should be entered on the APR only if schools are public target schools (Field 23), according to APR guidelines. Current data organization for this field shows that NCES school ID numbers are used for every high school that has students in the program. APR guidelines require that target schools that are private and parochial be entered using certain codes (e.g., a string of twelve sixes), as should target schools that have no NCES number. Most of the entries should be a string of twelve nines, which reflect non-target schools; these are most of the schools listed in the APR to which the researcher had access. Resolving this discrepancy with the data organization regarding target and non-target schools is key; it would assist better in the tracking of students who fall within various school types and would help in the analysis of comparing students in public target schools with those in other target-school types as well as in non-target schools when determining the effectiveness of the program.

Institute Measures to Monitor Intervention Drift

Atul Gawande, in his *The Checklist: How to Get Things Right*, discusses the importance of checklists in the everyday grind of one's work environment. These simple accountability measures, he asserts, help to avoid what could become huge problems down the professional road. A renown medical professional, Gawande has led several research efforts that support the strict use of the checklist in the surgery room, which has led to lower death rates, lower complication rates, and decreased infection rates (Mukherjee, 2018). Though no particular one item on a surgery checklist was ever solely responsible for better outcomes, the synergistic effect of all items working together became particularly impactful. Small things—like washing hands, making sure the instruments were sterilized, and making sure the right patient was on the table—served as necessary items to confirm before the more life-changing surgical procedure commenced. At its core, the idea is lodged in the reality that people, though well intentioned, are human, subject to error, and can easily fall prey to treatment drift (i.e., a slow but gradual straying away from prescribed treatment protocol).

In this same spirit, the same idea may be translated to some aspects of the UBMS program. Checklists stressing overarching ideas of the program could be considered to mitigate challenges faced on a regular basis. One indeed understands the mammoth task that UBMS program leaders face on a day-to-day basis to meet the needs of its student clientele. However, program leaders are only human and might benefit from this overall sense of checks and balances, lessening the possibility of intervention (i.e., treatment) drift. One example in particular stands out.

Especially during the period covering the bulk of this study, where subcontractors ran the program from 2017–2022 (see Figure 5), such a notion could have come in handy. Intentional and careful communication and follow up through main-idea checklists with the leadership of Steppingstone Scholars, the subcontractors, could have conveyed the importance of incorporating target schools more into the program's profile. Subletters—whether leasing apartments, cars, or STEM programs—tend to have their own ideas regarding what constitutes appropriate behavior unless lessors provide a clear and cogent understanding of the "lease" terms. In other words, general outcome checklists could be referenced and revisited at various junctures to remind program leaders of the overall mission and allow for mid-course correction before APRs are due to ED.

Resolve Missing Data

As an extension to the discussion in the Limitations section in chapter 4, a note in general may be helpful to program leadership concerning missing data. In a number of instances in the APRs, several pieces of data are not available. While it is not expected that 100% of the information for all students will ever be at the researcher's disposal, it is expected that a great deal of information will, especially for those assigned a PSE cohort. For these are the students who will go on to pursue postsecondary education and whose records will shine a light onto how effective or ineffective the program appears to be over time. Program leadership may locate some internal auditing software, which could flag instances early on when data become missing. Software could also be used to fill in data more fully along the way, alerting leadership of data gaps at predetermined checkpoints during the program (e.g., summers, fall, etc.).

Revisit How Program Delivery Between UB and UBMS Differs

Results from the first two research questions reveal that there is no significant difference between Temple's UB and UBMS students with regard to the proportion of them who completed advanced math courses and who achieved math proficiency on state assessments. One could argue that UBMS students should perform significantly higher in these categories compared to their UB counterparts since the aim of the former program caters specifically toward strengthening the STEM base of its students. One could imagine that administrators may become tempted to offer the same services for both programs since both run concurrently.

Since both programs are technically different in concept, though, leadership may want to spend time resolving internally how delivery of services might vary—even slightly—to push UBMS students toward ends that are distinct from those in the UB program. Should UBMS students receive more SAT math preparation? Should they be encouraged more to pursue tutoring in math courses during the academic year? Some brainstorming among leadership concerning how expectations and program delivery between both programs should differ would not be wasted energy. Though these discussions may not translate into a significant moving of the needle when comparing both groups along math- or STEM-related lines in general, it is vital to conceptually defend how both modes of delivery alter, even if run by the same administration.

Educational Implications

For Principal Investigators, Program Administrators, and Statisticians

Making Use of Quantitative Minds. Programs like UBMS depend on the expertise and foresight of various actors on several fronts. From grant writers to those having boots on the ground, these contributors have to stand arm in arm in order to impact the lives and performances of the students they serve. Particularly in programs that are not controlled as much by federal dollars, much leeway can be taken with including nontraditional minds in the formative phase of program setup. As assessment is a vital component of such programs, being deliberate in including those with an evaluative bent at the outset of program goal setting would be ideal in the grand scope of operation. Trained minds in fields like statistics and data analysis would indeed be beneficial. Not only could they provide guidance on variables needed for the assessment, but they could also convey how the data should be collected, lending their computational know-how to interpret and visualize results. Principal investigators (PIs) and program administrators not only have to welcome those with this kind of statistical prowess in program evaluation, but these leaders have to intentionally seek out those with this expertise. This widening of the circle to include an extra set of arms would bode well for these programs, which may not have seen the value in pulling from these quantitative minds heretofore.

In the current study, for example, a variable dubbed “At Risk: Low Grade Point Average at Initial Time of Selection,” is entered as a “1” if the GPA is 2.5 or less and a “2” if it is above 2.5. This means a student receives a “2” if they have a 2.6 and also a 3.9. This leads to such a wide range of GPAs for each subgroup, which hardly allows for the attainment of any significant analysis when investigating these students within these 2 separate batches. From a statistical standpoint, this is not as useful as simply stating what the student’s GPA is at the outset of the program. This allows the statistician to be in control of working with the data in its raw form, conducting related tests, and forming inferences. If the data analyst were in on the decision-making conversations about assessment, issues like this could be avoided.

Other times, depending on program structure, PIs and administrators have limited choice with respect to data they are required to report, especially if the program is like UBMS, which is backed by federal dollars. Nevertheless, they may still call upon those with statistical training. Leaders must remain transparent regarding what types of data are available and how statisticians can take what is provided and analyze it the best way possible, using as many cutting-edge methodologies as possible. Even in situations where data categories are already set in stone, the trained statistician can work with what is available and offer sound analysis. As long as leaders are true to their program theory and are vigilant about collecting data from theory, techniques like path analysis and multivariate regression remain viable options. Further, quantitative minds can work with administrators in locating software to assist with automating data collection, which would reduce the amount of missing data as well as minimize any errors based on human data entry.

Seeking Talent. Those dwelling in quantitative spaces may very well jump at opportunities to offer their computational and evaluative service to programs like UBMS. Often, the only barrier is the lack of knowledge of these programs and their willingness to be assessed. Graduate students with this background and expertise would relish the chance to try out their wings of assessment, but they do not have the inside track on who needs the assistance. An easy solution is for program administrators at various universities to issue a call for evaluation within their own university community. Such appeals for evaluation would resemble campus-wide email blasts concerning any other type of employment opportunities. Interested parties would simply respond to emails by making formal application to programs, undergoing interviewing protocols, and delving into learning about the programs and their mission. Depending on the level of involvement (i.e., if done for a university degree), a formal clearance is needed from the IRB, which is often reduced to an email positing that the study will be a secondary analysis with all sensitive information redacted from datasets. As long as no human subjects are involved (i.e., mixed methods approach), then the researcher has no hoops through which to jump in that respect.

Using resources at one's own university is commendable and makes for a tremendous sense of interdependence, knitting together people pockets within the college whose paths would probably not cross otherwise. Of course, if included as part of graduate student work for the degree, work can be "chalked up" as free labor. The degree is remuneration for services rendered. If work is performed using faculty expertise, however, a modest fee may apply and would be budget dependent. The idea is that programs would place themselves in positions where they can be evaluated without going outside of the confines of their universities. Even if they solicit assistance outside of university borders via these same email marketing strategies, administrators' actions in seeking quantitative assessment are gestures that highlight professionalism and a readiness to grow.

Taking a Step Back. In this particular project, the alliance between program administrators and the analyst was vital, not simply to satisfy requirements for a degree but to ensure that the program was given an even-handed assessment. Analyzing program data is a journey along a slippery slope. One must gain the trust of those whose program is being assessed. Since no program is perfect, it is the analyst's responsibility to convey a sense of trust, as administrators are exposing themselves to possible critiques that suggest the program is coming up short in some areas. Analysts must slow down enough to learn about the program's history and consider the context in which the data is to be analyzed. Hence, conversations about "nothing" may be par for the course to establish said trust in order to move forward.

Analysts must be willing to take risks. Simply reaching out to program administration in a thoughtful and sincere manner to inform them of a willingness to assess the program may be all that is needed to start the evaluative ball rolling. Thankfully, Temple's doctoral program is structured in such a way that suggests to students that pursuing program evaluation as a dissertation topic is a possibility. The

Research for Change course (EDAD 8636) provided the foundation necessary for those wanting to explore endeavors to evaluate programs; advisory faculty were open to allow for a finding of the way to do so; and program administration was willing to make the data available. It may be that programs have never undergone a rigorous protocol of assessment and may not have even considered it to be something that is needful. Administrators may only be used to gathering data and sending them elsewhere as part of the requirement to maintain funding, not really aware of areas that need improvement and also those in which they are on target.

Analysts must also be persistent. The UBMS administration was tremendously supportive of the project; however, it had its own day-to-day jobs to attend to. As a result, several follow-up efforts were necessary. Even in this, some emails were not returned and some voicemails were not responded to. One must learn quickly to develop thick skin when evaluating programs and not take the silence personally. Try again. Send another email. Say thank you. Leaders can want top-tier quantitative feedback but may have little time to dedicate to helping analysts do their job. This becomes one of the hurdles to negotiate on the road of program evaluation, and the astute researcher finds a way to figure it out.

Finally, data analysts must be communicators par excellence. There may already exist mild tension between program administrators and statisticians or their kind. The latter is often assumed to dwell in an Einsteinian world fraught with numbers and theories that are unable to be understood by the non-scientist. It becomes paramount for the analyst to stay true to the tenets of employed techniques of analysis but be adept at writing and explaining results in a way that can easily be consumed by program administrators or other non-quantitative onlookers. Walking this tightrope is perhaps the most challenging—even more so than analyzing the data themselves. Those running the program have a basic desire to know what all the statistical brouhaha is all about or to understand what the study suggests for daily operations. To the degree the analyst can offer meaningful yet honest interpretations of findings becomes of utmost importance. Last, delivering "bad news" to administrators about their program can always be conveyed in a positive manner, and the astute analyst will develop this knack with experience and over time. Thus, keeping lines of communication open is nonnegotiable.

For School Leaders

Initiatives such as Temple's UBMS program do what they can within their power to influence the lives and possible careers of FGLI high school students. Their longevity on the educational scene highlights their unwavering mission and bespeaks a sensitivity in helping to level the STEM playing field for all. As crucial as programs like UBMS are to pushing students forward, their impact and reach is limited. Students' level of participation in the program varies. Programs like UBMS, as good and as well intentioned as they might be, may find it difficult to shoulder the weight of single-handedly making a significant impact in students' postsecondary and career trajectory. They need help.

A certain amount of STEM signaling from principals may assist in keeping students dialed in and focused on the overall STEM goal. Such signaling from these leaders involves stressing to the entire school community that STEM education remains a high priority in schools, along with other hot-button items such as bullying, diversity, and democracy. Principals wield the ability to set the campus tone as it relates to clarifying academic expectations and to encouraging faculty to speak STEM. This tone setting very well may include championing priorities such as STEM field trips, STEM guest speakers, and annual science and math fairs; moreover, principals' decisions regarding what receives budgetary support could forge or weaken a viable STEM atmosphere at the school (Owens et al., 2015). Faculty and students alike would hopefully feel a sense of support from such signaling from school leaders and feel a renewed energy to stay the STEM course.

For Teachers

Relatedly, one way in which school leaders can place some shape around fulfilling the needs of programs like the UBMS program is by fostering strong partnerships between teachers in the school and the program itself through accountable mentorship. When students are within the sight of program leaders during summer sessions, the influence from the program in keeping students on track for success is apparent. Interestingly enough, partial results from Research Question Three show that most of the students (36.4%) who only participated in the program during the academic year only (i.e., no summers) failed to achieve a rigorous course of study by the time they graduated from high school. This lack of summer interaction between students and the UBMS program may seem to suggest that more support may be necessary in the reinforcement of the program's aim and the doubling up of services during the academic year to make up the difference. In other words, if students choose not to participate in the program during the summer, they should still experience a sense of support from the program during the academic year.

In this vein, the idea of enlisting assistance from vetted teachers at high schools that harbor UBMS students is not farfetched. Doing so would echo the model employed in the Pipeline Program in the Center of Excellence at Morehouse College in the late 1990s. This program, funded by the Department of Defense and run by the Physics Department, mirrored the UBMS program to a large degree. It had, however, the added program benefit of maintaining contact with and providing support for students during the academic year in a slightly different manner. Math or science teachers, where Pipeline students attended, were recruited and paid to serve as high school mentors and provide a sense of program continuity throughout the year (Dixon, 1996-2002). Mentors met with students at least once a month to check in and get a feel for any challenges students were facing and kept program coordinators in the know if any problems arose. Mentoring forms were submitted to coordinators monthly. This also created another reason for teachers to be in touch with students' parents regarding the program; communication between them was crucial as it related to students' goals within or outside of school walls.

Mentors also offered guidance in the form of course selection, encouraging students to stay on a STEM path and even becoming many of the students' teachers in a number of their high school courses. Any students falling off the STEM track could be identified quicker with high school mentors than with off-campus program leaders, potentially reducing possible program attrition rates. Further, many of these same teachers would be hired during summers, along with college faculty, to teach STEM courses that students would enroll in during the following academic term.

Of course, the Pipeline Program had a built-in budget to financially incentivize teachers to assume this program liaison role. If Temple's UBMS program has discretionary funds that it can use to fuel this aspect of mentorship, money for such might be well spent. Especially as relationships ramp up in the near future between the program and target schools, this extra layer of propping for students would likely contribute to keeping STEM pipelines unclogged or, at the least, relatively passable. Whatever decision is reached, it would be admirable for SIPs like the UBMS program to find unique ways in which to include on-site, high school teachers in the well-known STEM struggle among FGLI students (Craig et al., 2019).

For School Districts

Although Temple's UBMS program strives to make a difference in the STEM academic pursuits of students at the high school level, many of the efforts to effect change must occur at pre-secondary levels. District leaders are arguably in the most influential position to stress the importance of STEM education not only to its high schools but also to elementary and middle schools. So that individual school leaders do not have to feel alone in towing the STEM line at their respective schools, district leaders can do much to reinforce this priority on a wider level. Newsletters, email blasts to the school community, communication with parents, and social media presence do much to keep the STEM embers lit on a broader scale than by focusing on a single school. Forging this central message across grade levels in the district provides school leaders the right of way to make STEM a priority on their master planning schedule and sets the stage for teachers to fold STEM into their curricula in the most level-appropriate way.

Further, district leaders remain perched on a unique ledge with regard to the ability to forge relationships between their schools and universities that run SIPs. Contestably, the most effective district leader is the one who realizes that—to reference John Donne's famous poem—no school district is an island, entire of itself. As such, these leaders can work wonders to foster alliances between surrounding universities and schools within the district in order to maximize resources and social capital, especially if schools are located in areas where FGLI representation is high.

This viewpoint is consistent with the idea of the community schools systems approach, whose overriding ideology is lodged in the belief that vibrant connections between the school system and local resources become a boon for all students, families, and communities (Maier et al., 2017). One of the four tenets associated with this educational working frame is the use of integrated student supports (ISSs), which are programs or services that schools arrange with outside organizations to meet the needs of students; notably, said programs are keen on addressing structural barriers that stand in the way of students' educational success. As districts make efforts to stay cognizant of ISS-centric initiatives like the UBMS program, it is able to marry the hefty resources from local universities with district schools that may have below-par supply in order to bridge the STEM access gap. This approach that districts can capitalize on becomes even more enriched by the phenomenon that several well-to-do colleges and universities are located in areas where the surrounding population of families and students are of low income. And universities benefit from such a partnership with district schools in that students may often matriculate to the very universities in the community that have invested into shaping their social and academic selves, creating a win-win for both the district and the postsecondary institution itself.

District leadership in Louisville, Kentucky instituted efforts to leverage partnerships with the local university to strengthen STEM pipelines in nearby schools. In the early 2000s, The J.B. School of Engineering at the University of Louisville initiated a K–12 STEM outreach program, whose sole intent was to create a bridge for students in the surrounding urban Jefferson County Public School (JCPS) System. With a mission of exposing underrepresented young students to the world of engineering and technology, the initiative reached out to elementary, middle, and high schools in the district, eventually becoming set up in over fifteen schools and impacting some 2,000 students after only four years of being established (Ralston et al., 2013).

Using approved curricula at all pre-secondary and secondary levels, the program's reach was obvious. In response to teacher and parent requests, summer camps—including robotics camps—were added to provide additional support for students. Though no formal assessments were offered at the time of this particular study, data showed an increase in student participation in the program at the primary pipeline high school and an increase in math and science scores on the Kentucky Core Content Test at one of the elementary schools, all of whose students used the program-vetted curriculum. The strategy to strengthen the STEM pipeline among students involved a consortium of a willing engineering school with resources, a fearless and engaging school district, a dedicated band of public-school teachers committed to STEM, and other industry partners. In sum, "partners, working together through their common interest in STEM education, were able to achieve results that would be difficult for any one of them to achieve working independently” (p. 160).

For Funding

As well-intentioned and as dedicated as these partnerships are that address the STEM pipeline shortages in schools, efforts often move along at a snail’s pace without monetary resources to reinforce plans. While universities may indeed have budgets set aside to facilitate such partnerships involving key actors in STEM, more funds are generally needed to undergird these initiatives on a long-term basis. While some of this funding is available from federal agencies, it tends to be rewarded after fierce competition, the spoils of which depend on whether applicants are trained or experienced in grant writing. Alternatively, businesses and equity collectives have significantly stepped in to fill the gap and laid millions of dollars on the line to provide the desperately needed resources to solidify the discussed partnerships between schools, SIPs, universities and colleges, local government, and other philanthropic organizations.

Primarily purveyors of diversity, equity, and inclusion, these collectives recognize their roles in the community and understand that STEM strides to be made among disadvantaged youth have to remain steady. Hence, the investment of resources over time is a crucial component in the STEM success equation. Once could surmise that a portion of Temple’s UBMS students have reaped the benefits of such financial backing through one of the most recent initiatives buttressed by the Philadelphia STEM Equity Collective and spearheaded by GlaxoSmithKline, whose unselfish $10 million contribution to STEM programs over the next decade will surely be the break that city students have dreamed of (Muse, 2020). Leadership within the Collective has vowed to ensure that students who will receive strongest support are those representing a huge cross-section across the FGLI landscape. As local programs crystallize their strategies and get their planning ducks in a row to determine which collaborations are critical to their goals, the financial support from efforts like these helps to cement the dreams, hopes, and aspirations of students, teachers, districts, and their surrounding communities at large.

From the perspective of the SIP, federal financial support for Temple's UBMS program, of course, is the lifeblood of the program's existence. Having to reapply for funds roughly every five years to keep the program's fiduciary stream steady, program leaders could feel overwhelmed with meeting the needs of students who require seemingly unlimited support and with balancing no-nonsense mandates from federal juggernauts who hold the purse. Such becomes the life of these program leaders and administrators, who often work into the wee hours of the morning and sacrifice much of their own personal and social life, handling the business associated with these programs. The funding component of the program, especially if emanating from federal sources, is a two-edged sword. It serves as a financial boon for those responsible for pushing a STEM agenda in the public schools, but it also exists as a constant reminder that "Big Brother" is watching and always expects strict adherence to federal guidelines.

For Policymakers

State. The referenced partnership between the University of Louisville and the JCPS System is only one branch of a much larger statewide tree, whose efforts to address STEM disparities in Kentucky are admirable. Its academic standards for mathematics, for example, span grade levels, realizing the need for consistency over time to ensure student comprehension. Section 704 KAR 8:040 adopts into law these mathematics standards, so as to assure a minimum statewide level of students' math competence before graduating (2018). Although a law such as this emboldens states to strengthen students' mathematical foundation and literacy, it is far from a measure to dictate curriculum within classroom borders. States pass the baton to districts and local schools to put some curricular shape around standards to maximize student mathematical growth. A chief aspect of Kentucky's law is to ensure that the standards are aligned from elementary to middle to high school to postsecondary education so that students can reach a level of success at each level.

A significant challenge in determining how state policymakers handle the prioritizing of STEM education lies in how they define STEM at its core. Because no one STEM definition pervades nationally—and rightfully so, according to many—states enjoy a certain latitude in how they weave the STEM thread through their district and local needles. Whether they view the field as one simply unto itself or as integrated with other disciplines regulates how the policy is revealed in each state. Hence, acronyms like STEAM, STREAM, and STEM-H reflect different states' perceptions about the intertwining of STEM with the arts, reading (or religion), and health, respectively (Ingram, 2019). Maintaining varying conceptual differences about what STEM should be, in turn, affects policies emanating out of states and eventually contributes to students' competence in their preparation. While states can do little by way of forcing districts to implement a particular STEM agenda, policymakers are expected to provide a sturdy base from which districts can operate in order to guide their student clients toward STEM success. As Temple's UBMS program depends on cooperation between local schools and universities as well as steady funding, state leaders who introduce initiatives that bolster these aspects of the STEM journey display prudent judgment regarding the challenge.

Zinth and Goetz (2016) advise that state STEM policy approaches are only as effective as their ability to address three key elements. First, although quite a number of STEM initiatives may exist from district to district, many go unnoticed because no efforts are in place to close the loop of communication concerning them; hence, *coordination* is important to exploit these resources. A single, statewide hub might be useful to centralize efforts dedicated to STEM educational matters. Second, legislation is needed to secure and maintain *resources* to sustain STEM efforts across the state. Funding opportunities may be useful for shoring up relationships between local schools, universities, industry, and necessary for meeting staffing needs in the coordination phase. Finally, *evaluation* is vital for policymakers to consider when fostering STEM impact. Often, districts choose STEM learning tools simply based on cost and not on quality; further, STEM programs across the state tend to focus only on matters of the day, taking little time to breathe and assess their impact. As funds allow, this state-based hub must infuse and nurture an evaluative component to stay abreast of what works and what does not.

Federal. Federal policymakers are at fewer odds concerning settling in on an operating definition of STEM, unlike state leaders. The working definition—which accounts for computer science—arguably makes policymaking on the national level a more manageable endeavor. Still, no policy at the federal level will have enough teeth to affect what directly transpires in the classroom. Initiatives are generally restricted to providing financial support for students and professional development opportunities by way of grants for STEM programs, for which state leaders vie, and teacher-training opportunities.

In accordance with the UBMS study's findings, federal dollars would go far in investing in SIPs whose end goals include having students obtain a rigorous course of study. A critical indicator of STEM interest, this programmatic element sets the stage for college success and career persistence in the field. Federal policy that accentuates teachers' STEM professional development and their associations with external organizations and universities is primary in order to equip major actors in STEM with the tools needed to support students.

Federal policy concerning agendas to strengthen STEM on a national front defers to state wishes. While much may go into the planning behind what national leaders want to accomplish in STEM educational circles, federal legislation is only as powerful as its ability to empower state agencies to carry out their own STEM missions. For instance, the Obama-Biden Race to the Top stratagem provided a pool of funds for states to bolster their STEM outreach throughout their borders. Hence, states were now able to exert their STEM influence in a more systematic way, ideally making more opportunities available for students in demographics historically overlooked. Further, leaders for the initiative made states' proposals, commentary, and amendments accessible "for [other] states to learn from, researchers to analyze, the media to probe, and the public to watchdog" (Hess & Weiss, 2015, p. 52).

More recently, the Biden-Harris administration launched the Raise the Bar: STEM Excellence for All Students measure, a national effort again bent on pushing the STEM agenda in schools. The mantra of the initiative continues to echo the need for developing students in rich and STEM-rigorous classes with hopes of landing on academic success over time. Though its foci cater to all of the country's students, its dedication to students of color and students with disabilities remains prominent (Kyaw, 2022). The ED-backed movement has received support and commitments from a cadre of organizations from across the nation to partner with states and districts. These types of federal policy strategies enable projects like Temple's UBMS program to remain relevant, vibrant, and sensitive to the needs of an ever-changing FGLI population.

For Future Research

A Merging of the Minds. Although this study is devoted strictly to quantitative analysis, it was done so in an attempt to begin "balancing out" the volume of qualitative work done to assess the UBMS program in the literature. A more thorough study of the program, however, would glean from experts in both qualitative and quantitative fields. As much as statisticians and data analysts may praise such methods as presented in this study, the same methods are limited in what they may convey. They are only able to impart a partial narrative. Hence, many of the gaps created from the implementation of the techniques of analysis may very well be covered through qualitative means. UBMS and programs like it, then, are ideal targets for mixed-methods research. For example, the third research question shined the light on how students' grade level was a significant negative predictor for whether students attained a rigorous course of study. Even a closer look at the data (see Figure 19) afforded only stabs at possible theories that could have contributed to observed trends. Incorporating expertise from minds trained in inquiry-based methodologies might reveal priceless insight behind the rigid data scenes, putting qualitative flesh on quantitative bones.

Qualitative Foci for the Current Project. For this project, interviews with former program coordinators in the Steppingstone Scholars Program would be invaluable to understand many of the data results, especially with regard to community service and its seeming negative correlation with advanced math course taking. In order to contextualize results presented herein, future studies could be poised to interrogate program leadership to zero in on program morale overall and issues concerning missing data. Interviewers must be able to exploit their skills to confirm idiosyncrasies in the data that seem to be related to the advent of COVID-19.

As most of the analysis is based on the time frame in which this administration oversaw the program, much of the data gathering would possibly be in the form of said interviews of leaders and focus groups of past participants. Social media would work wonders in locating these students, and technology in general would make most of these interviews and focus group sessions doable in a reasonable amount of time. Once explanations for the study are given and waivers are signed, a wealth of data would likely surface. Through these methods, one would also obtain clarity on the second research question. It is still not as apparent how delivery of both UB and UBMS programs differs, as the fine-tuned distinctions between both are not obvious in the literature or via cursory research. Probing administrators in this respect would tend to make such contrasts more transparent.

Data Management for Other Outcomes. As UBMS program administrators are minimally beholden to reporting on outcomes listed on the APR, they may still determine that monitoring other variables would prove beneficial as they make cases to convey their success in order to establish rationale for continued funding. Services such as tutoring, counseling, and mentoring play critical roles in the lives of UBMS students and, no doubt, contribute to their success in high school and postsecondary realms. To get at these measures, administrators have a number of options for collecting these data. To capture data regarding tutoring, administrators can administer surveys to all those who have been tutored at some point during UBMS studies. Such surveys can get at students' feelings about their tutoring experience and if they felt that it contributed to their academic progression. With regard to academic counseling, select participants—past and present—may be interviewed to field questions regarding how they thought counseling impacted (or did not impact) their course choices and decision to pursue postsecondary education. Further, focus groups involving mentors themselves, students, and parents can help to corroborate or refute ideas about the effectiveness of mentorship on students during their program tenure. These notions only represent a sample of methodologies that may be employed to foster analysis of data variables that are omitted from the APR but may be characterized as equally as crucial to understanding the mission of the program.

Concluding Remarks

The UBMS program has provided a sense of guidance and support for no small number of FGLI students in Philadelphia and beyond its city borders. One might consider the country's priorities regarding STEM intervention as bittersweet. On one hand, offering such services to one of the most marginalized sectors in society reflects a certain sensitivity and nobility on the part of the country's leadership as it tries to maintain its edge in all things technological; advocating for and addressing issues regarding STEM access continue to forge a narrative of changemaking along the lines of social justice as seen through an academic lens. Contrarily, the fact that the need for this type of intervention remains as strong now as it was in the mid-nineteenth century gives one pause and could be interpreted as a sad commentary of social stagnancy—a Groundhog Day of STEM sorts. The time is different, but the issue endures. As domestic pressures threaten the stability of the family and foreign factors loom large, the nation will probably continue to push some version of a STEM-based agenda. And unlike the name of former President Obama's initiative, the journey to the STEM top will likely be anything but a race; if past is prologue, the journey will presumably be a slow and steady trek—a marathon—requiring assistance from many directions to support the next generation of FGLIers.

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APPENDIX A

R CODE FOR SELECT FIGURES

Included in Appendix A are the R codes used to produce relevant figures in the dissertation. Such codes were developed on the RStudio platform.

Coding for Figure 1

The following code was used to create Figure 1: U.S. Undergraduate First-Generation, Low-Income Students by Select Characteristics.

```
Race <-
  c(
    “Hisp/Lat” = 25,
    White = 46,
    Asian = 6,
    “Afr-Am” = 18,
    Alaska = 1,
    “NH/PI” = 0.5
  )
Sex <- c(Male = 40, Female = 60)
Age <- c(“30 or older” = 28, “Younger than 30” = 72)
Dependent <- c(“With Dep” = 30, “Without Dep” = 70)

plot_race <- enframe(Race, name = “Race”, value = “Percentage”) |>
  mutate(Race = fct_reorder(Race, Percentage, .desc = TRUE) |> fct_rev())
|>
  ggplot(aes(Race, Percentage)) +
  geom_col(fill = “#0A9F9D”)  +
  geom_richtext(
    aes(label = Percentage),
    size = 2,
    vjust = 0.5,
    hjust = -0.1,
    label.color = NA
  ) +
  theme_minimal() +
  coord_flip() +
  theme(axis.title = element_text(size = 6.5)) +
  theme(text = element_text(size = 6)) +
  scale_y_continuous(limits = c(0, 100)) +
  labs(title = substitute(paste(bold(“Race”))),
       x = NULL) +
  theme(plot.title = element_text(hjust = 0.5, size = 8))

plot_sex <- enframe(Sex, name = “Sex”, value = “Percentage”) |>
  mutate(Sex = fct_reorder(Sex, Percentage, .desc = TRUE) |> fct_rev()) |>
  ggplot(aes(Sex, Percentage)) +
  geom_col(fill = “#CEB175”)  +
  geom_richtext(
    aes(label = Percentage),
    size = 2,
```

```
    vjust = 0.5,
    hjust = -0.1,
    label.color = NA
  ) +
  theme_minimal() +
  coord_flip() +
  theme(axis.title = element_text(size = 6.5)) +
  theme(text = element_text(size = 6)) +
  scale_y_continuous(limits = c(0, 100)) +
  labs(title = substitute(paste(bold("Sex"))),
       x = NULL) +
  theme(plot.title = element_text(hjust = 0.5, size = 8))

plot_age <- enframe(Age, name = "Age", value = "Percentage") |>
  mutate(Age = fct_reorder(Age, Percentage, .desc = TRUE) |> fct_rev()) |>
  ggplot(aes(Age, Percentage)) +
  geom_col(fill = "#E54E21")  +
  geom_richtext(
    aes(label = Percentage),
    size = 2,
    vjust = 0.5,
    hjust = -0.1,
    label.color = NA
  ) +
  theme_minimal() +
  coord_flip() +
  theme(axis.title = element_text(size = 6.5)) +
  theme(text = element_text(size = 6)) +
  scale_y_continuous(limits = c(0, 100)) +
  labs(title = substitute(paste(bold("Age"))),
       x = NULL) +
  theme(plot.title = element_text(hjust = 0.5, size = 8))

plot_dependent <-
  enframe(Dependent, name = "Dependent", value = "Percentage") |>
  mutate(Dependent = fct_reorder(Dependent, Percentage, .desc = TRUE) |>
fct_rev()) |>
  ggplot(aes(Dependent, Percentage)) +
  geom_col(fill = "#6C8645")  +
  geom_richtext(
    aes(label = Percentage),
    size = 2,
    vjust = 0.5,
    hjust = -0.1,
    label.color = NA
  ) +
  theme_minimal() +
  coord_flip() +
  theme(axis.title = element_text(size = 6.5)) +
  theme(text = element_text(size = 6)) +
  scale_y_continuous(limits = c(0, 100)) +
  labs(title = substitute(paste(bold("Dependent Status"))),
       x = NULL) +
  theme(plot.title = element_text(hjust = 0.5, size = 8))

(plot_race + plot_sex) /  (plot_age + plot_dependent)
```

Coding for Figure 2

The following code was used to create Figure 2: U.S. College Enrollment: Continuing-Generation and First-Generation, Low-Income Enrollees.

```
tibble(
  grad = c("Continuing-generation students", "FGLI students"),
  n = c(70, 30)
) |>
  uncount(n) |>
  waffle_iron(aes_d(group = grad), rows = 10) |>
  mutate(label = fontawesome('fa-university')) |>
  ggplot(aes(x, y, color = group)) +
  labs(title = substitute(paste(bold(
    "For every 100 U.S. college students"
  ))),
  x = NULL) +
  theme(plot.title = element_text(hjust = 0.5)) +
  geom_text(aes(label = label), family = 'fontawesome-webfont', size = 5) +
  coord_equal() +
  scale_color_manual(
    NULL,
    values = c("#0A9F9D", "#CEB175"),
    labels = c("CG students", "FGLI students")
  ) +
  theme_void(base_family = 'Times New Roman', base_size = 10) +
  theme(legend.position = "bottom") +
  theme(plot.title = element_text(hjust = 0.5))


tibble(grad = c("Continuing-generation", "First-generation"),
       n = c(22, 8)) |>
  uncount(n) |>
  waffle_iron(aes_d(group = grad), rows = 10) |>
  mutate(label = ifelse(
    group == 'Continuing-generation',
    fontawesome('fa-university'),
    fontawesome('fa-graduation-cap')
  )) |>
  ggplot(aes(x, y, color = group)) +
  labs(title = substitute(paste(bold(
    "Of these 30 FGLI Enrollees"
  ))),
  x = NULL) +
  theme(plot.title = element_text(hjust = 0.5)) +
  geom_text(aes(label = label), family = 'fontawesome-webfont', size = 4) +
  coord_equal() +
  scale_color_manual(
    NULL,

    values = c("#CEB175", "#E54E21"),
    labels = c("No graduation", "Completed degree")
  ) +
  theme_void(base_family = 'Times New Roman', base_size = 7) +
  theme(legend.position = "bottom") +
  theme(plot.title = element_text(hjust = 0.5))
```

Coding for Figure 3

The following code was used to create Figure 3: U.S. STEM College Enrollment: Continuing-Generation and First-Generation, Low-Income Enrollees.

```
tibble(
  grad = c("Continuing-generation students", "FGLI students"),
  n = c(80, 20)
) |>
  uncount(n) |>
  waffle_iron(aes_d(group = grad), rows = 10) |>
  mutate(label = fontawesome('fa-university')) |>
  ggplot(aes(x, y, color = group)) +
  labs(title = substitute(paste(bold(
    "For every 100 U.S. college students"
  ))),
  x = NULL) +
  theme(plot.title = element_text(hjust = 0.5)) +
  geom_text(aes(label = label), family = 'fontawesome-webfont', size = 5) +
  coord_equal() +
  scale_color_manual(
    NULL,
    values = c("#0A9F9D", "#CEB175"),
    labels = c("CG students", "FGLI students")
  ) +
  theme_void(base_family = 'Times New Roman', base_size = 10) +
  theme(legend.position = "bottom") +
  theme(plot.title = element_text(hjust = 0.5))


tibble(grad = c("Continuing-generation", "First-generation"),
       n = c(5, 15)) |>
  uncount(n) |>
  waffle_iron(aes_d(group = grad), rows = 10) |>
  mutate(label = ifelse(
    group == 'Continuing-generation',
    fontawesome('fa-university'),
    fontawesome('fa-graduation-cap')
  )) |>
  ggplot(aes(x, y, color = group)) +
  labs(title = substitute(paste(bold(
    "Of these 20 FGLI Enrollees"
  ))),
  x = NULL) +
  theme(plot.title = element_text(hjust = 0.5)) +
  geom_text(aes(label = label), family = 'fontawesome-webfont', size = 4) +
  coord_equal() +
  scale_color_manual(
    NULL,

    values = c("#CEB175", "#E54E21"),
    labels = c("No graduation", "Completed degree")
  ) +
  theme_void(base_family = 'Times New Roman', base_size = 7) +
  theme(legend.position = "bottom") +
  theme(plot.title = element_text(hjust = 0.5))
```

Coding for Figure 7

The following code was used to create Figure 7: Temple's Upward Bound Math and Science Students at a Glance, 2008–2021.

```
d <- read_csv("anonymizedUBandUBMS.csv") %>%
  filter(Type == 2) %>%
  distinct(id, .keep_all = TRUE) %>%
  mutate(
    race_american_indian = factor(
      Race1,
      levels = c(1, 2),
      labels = c("American-Indian", NA)
    ),
    race_asian = factor(Race2, levels = c(1, 2), labels = c("Asian", NA)),
    race_black = factor(Race3, levels = c(1, 2), labels = c("Black", NA)),
    race_white = factor(Race4, levels = c(1, 2), labels = c("White", NA)),
    race_hawaiian = factor(
      Race5,
      levels = c(1, 2),
      labels = c("Hawaiian/Pacific Islander", NA)
    ),
    ethnic_hisp = factor(
      Ethnic,
      levels = c(1, 2),
      labels = c("Hispanic", NA)
    )
  ) %>%
  unite(
    Race,
    ethnic_hisp,
    race_american_indian,
    race_asian,
    race_black,
    race_white,
    race_hawaiian,
    sep = ", ",
    na.rm = TRUE
  )

bind_rows(
  d %>%
    count(Race) %>%
    mutate(
      variable = "Race",
      Category = fct_reorder(Race, n) %>%
        fct_rev() %>%
        fct_other(drop = "") %>%
        fct_rev()
    ) %>%
    arrange(Category),

  d %>%
    count(GenderCD) %>%
    mutate(
      variable = "Gender",
      Category = factor(
        GenderCD,
        levels = c(1, 2),
```

```
        labels = c("Male", "Female")
      ) %>% fct_reorder(n)
    ) %>%
    arrange(Category),

  d %>%
    filter(!(EligibilityCD == 0)) %>%
    count(EligibilityCD) %>%
    mutate(
      variable = "Eligibility",
      Category = factor(
        EligibilityCD,
        levels = c(2, 3, 4, 1, 5, 6, 7),
        labels = c(
          "Low-income only",
          "First-generation only",
          "At risk for academic failure only",
          "Low-income and first-generation",
          "Low-income and at high risk for academic failure",
          "First generation and at high risk for academic failure",
          "Low-income, first-generation, and at high risk for academic"
        )
      )
    ),

  d %>%
    count(EnterGradeLV) %>%
    mutate(variable = "Grade Level", Category = factor(EnterGradeLV))
) %>%
  select(-Race,-GenderCD,-EnterGradeLV,-EligibilityCD) %>%
  mutate(variable = fct_inorder(variable)) %>%
  ggplot(aes(n, Category)) +
  geom_col(aes(fill = variable)) +
  geom_richtext(
    aes(label = n),
    family = "serif",
    size = 10 * 0.8 / 2.845276,
    label.padding = margin(0.5, 0.5, 0.5, 0.5),
    label.margin = margin(l = 2),
    vjust = 0.5,
    hjust = 0,
    color = "gray40",
    label.color = "NA"
  ) +
  facet_wrap(vars(variable),
             scales = "free",
             nrow = 2,
             ncol = 2) +
  scale_y_discrete(NULL, labels = \(x) str_wrap(x, width = 25)) +
  scale_x_continuous("Count", expand = expansion(mult = c(0, 0.20))) +
  scale_fill_manual(values = c("#CEB175", "#0A9F9D", "#E54E21", "#6C8645"))
+
  theme_minimal(base_family = "serif", base_size = 8) +
  theme(
    plot.title = element_text(hjust = 0.5, face = "bold"),
    strip.text = element_text(
      face = "bold",
      color = "gray30",
      size = 12
    ),
```

```
    legend.position = "none"
  )
ggsave("ubms.pdf", width = 6.5, height = 8.5)
```

Coding for Figure 9

The following code was used to create Figure 9: UBMS Postsecondary Completion Percentages, 2017–2021.

```
library(tidyverse)
library(ggplot2)

df <-
  data.frame(
    Graduation = c("2017", "2018", "2019", "2020", "2021"),
    Percent = c(58.8, 61.1, 60, 71.4, 50)
  )
wesanderson::wes_palette("AsteroidCity1")
mycolors <- wesanderson::wes_palettes$AsteroidCity1[3]

head(df)

ggplot(data = df, aes(x = Graduation, y = Percent, group = 1)) +
  geom_line(col = mycolors) + geom_point(col = mycolors) +
  geom_text(
    aes(label = Percent),
    nudge_y = 4,
    size = 4,
    family = "serif"
  ) +
  theme_light(base_size = 12, base_family = "serif") +
  scale_y_continuous(
    "Percent Graduation \n Within 6 Years",
    limits = c(0, 100),
    labels = \(x) paste0(x, "%"),
    expand = expansion()
  ) +
  scale_x_discrete("Graduation Year of Cohort \n (6-Year Window)")
```

Coding for Figure 10

The following code was used to create Figure 10: Temple's Upward Bound and Upward Bound Math and Science Programs at a Glance.

```
library(tidyverse)

wesanderson::wes_palette("AsteroidCity1")
mycolors <- wesanderson::wes_palettes$AsteroidCity1[1:2]
tibble::tribble(
  ~ Category,
  ~ UBMS,
  ~ UB,
  # "n",   374,  483,
  "Asian",
  13.4,
  13.4,
  "Black",
```

```
  73.45,
  85.5,
  "Female",
  65.8,
  61.3,
  "FGLI",
  68.2,
  66.9,
  "Enter\nYear 9-10",
  93.3,
  94.4
) %>%
  pivot_longer(-Category, names_to = "Program") %>%
  mutate(Category = fct_inorder(Category)) %>%
  ggplot(aes(Program, value)) +
  geom_col(aes(fill = Program)) +
  geom_text(
    aes(label = round(value, 1)),
    color = "white",
    vjust = 1.5,
    size = 7,
    family = "serif"
  ) +
  facet_grid(cols = vars(Category), scales = "free_y") +
  scale_fill_manual(values = mycolors) +
  theme_light(base_size = 24, base_family = "serif") +
  theme(
    legend.position = "none",
    strip.background = element_rect(fill = "gray60"),
    panel.grid.major.x = element_blank()
  ) +
  geom_blank() +
  scale_y_continuous(
    "Percent",
    limits = c(0, 100),
    labels = \(x) paste0(x, "%"),
    expand = expansion()
  ) +
  scale_x_discrete(NULL)

ggsave("demographics.pdf", width = 9, height = 7)
file.show("demographics.pdf")
```

Coding for Figure 11

The following code was used to create Figure 11: Proportion of Students Taking Advanced Math Courses in High School.

```
d_advmath <- read_csv("anonymizedUBandUBMS.csv") %>%
  filter(!(PSECohort %in% c("8888"))) %>%
  select(id, AdvancedMath, Type, year) %>%
  filter(AdvancedMath %in% c("1", "2")) %>%
  arrange(id, year) %>%
  mutate(
    studentrownumber = row_number(),
    minstudentrownumber = min(studentrownumber),
    .by = id
  )  %>%
  filter(studentrownumber == minstudentrownumber) %>%
```

```
  mutate(
    Type = factor(Type, levels = c(1, 2), labels = c("UB", "UBMS")),
    AdvancedMath = factor(
      AdvancedMath,
      levels = c("1", "2"),
      labels = c("Completed", "Not Completed")
    )
  )

d_advmath %>%
  count(Type, AdvancedMath) %>%
  mutate(Proportion = n / sum(n), .by = Type) %>%
  filter(AdvancedMath == "Completed") %>%
  ggplot(aes(Type, Proportion)) +
  geom_col(aes(fill = Type)) +
  geom_richtext(
    aes(label = WJSmisc::prob_label(Proportion)),
    vjust = 0,
    color = "gray20",
    label.color = NA,
    family = "serif",
    size = WJSmisc::ggtext_size(15)
  ) +
  scale_x_discrete("Program") +
  scale_fill_manual(values = wesanderson::wes_palette(name =
"AsteroidCity1")) +
  scale_y_continuous(labels = WJSmisc::prob_label, limits = c(0, 1)) +
  theme_minimal(base_family = "serif", base_size = 15) +
  theme(legend.position = "none") +
  labs(title = "Proportion of Students Taking \nAdvanced Math Courses in
High School") +
  theme(plot.title = element_text(
    size = 15,
    hjust = 0.5,
    color = "gray20",
    face = "bold"
  ))
```

Coding for Figure 12

The following code was used to create Figure 12: Proportion of Students Across Programs Achieving Proficiency on State Math Assessments.

```
d_mathprof <- read_csv("anonymizedUBandUBMS.csv") %>%
  filter(!(PSECohort %in% c("8888"))) %>%
  select(id, HSProficientMath, Type, year) %>%
  filter(HSProficientMath %in% c(3, 4)) %>%
  arrange(id, year) %>%
  mutate(
    studentrownumber = row_number(),
    maxstudentrownumber = max(studentrownumber),
    .by = id
  )  %>%
  filter(studentrownumber == maxstudentrownumber) %>%
  mutate(
    Type = factor(Type, levels = c(1, 2), labels = c("UB", "UBMS")),
    HSProficientMath = factor(
      HSProficientMath,
      levels = c(3, 4),
```

```
      labels = c("Proficient", "Not Proficient")
    )
  )
ggplot(d_mathprof, aes(x = Type, fill = HSProficientMath)) +
  geom_bar(position = position_fill(reverse = TRUE))

d_mathprof %>%
  count(Type, HSProficientMath) %>%
  mutate(Proportion = n / sum(n), .by = Type) %>%
  filter(HSProficientMath == "Proficient") %>%
  ggplot(aes(Type, Proportion)) +
  geom_col(aes(fill = Type)) +
  geom_richtext(
    aes(label = WJSmisc::prob_label(Proportion)),
    vjust = 0,
    color = "gray20",
    label.color = NA,
    family = "serif",
    size = WJSmisc::ggtext_size(15)
  ) +
  scale_x_discrete("Program") +
  scale_fill_manual(values = c("#E54E21", "#6C8645")) +
  #scale_fill_manual(values = wesanderson::wes_palette(name =
"AsteroidCity1")) +
  scale_y_continuous(labels = WJSmisc::prob_label, limits = c(0, 1)) +
  theme_minimal(base_family = "serif", base_size = 15) +
  theme(legend.position = "none") +
  labs(title = "Proportion of Students \nAchieving Math Proficiency") +
  theme(plot.title = element_text(
    size = 15,
    hjust = 0.5,
    color = "gray20",
    face = "bold"
  ))
```

Coding for Figure 13

The following code was used to create Figure 13: Proportion of Students Beginning Postsecondary Education Immediately Following High School.

```
d_postsecondary <- read_csv("anonymizedUBandUBMS.csv") %>%
  filter(!(PSECohort %in% c("8888"))) %>%
  filter(PSEGradeLV != 0) %>%
  arrange(id, year) %>%
  mutate(
    studentrownumber = row_number(),
    minstudentrownumber = min(studentrownumber),
    .by = id
  )  %>%
  filter(studentrownumber == minstudentrownumber) %>%
  mutate(Postsec = fct_collapse(factor(PSEGradeLV), No = "9", Yes =
as.character(c(2, 3, 4, 5, 7, 10, 11)))) %>%
  mutate(
    Type = factor(Type, levels = c(1, 2), labels = c("UB", "UBMS")),
    Postsec = factor(
      Postsec,
      levels = c("Yes", "No"),
      labels = c("PursuingPost", "Not PursuingPost")
    )
```

```
  )

d_postsecondary %>%
  count(Type, Postsec) %>%
  mutate(Proportion = n / sum(n), .by = Type) %>%
  filter(Postsec == "PursuingPost") %>%
  ggplot(aes(Type, Proportion)) +
  geom_col(aes(fill = Type)) +
  geom_richtext(
    aes(label = WJSmisc::prob_label(Proportion)),
    vjust = 0,
    color = "gray20",
    label.color = NA,
    family = "serif",
    size = WJSmisc::ggtext_size(15)
  ) +
  scale_x_discrete("Program") +
  scale_fill_manual(values = c("#C18748", "#0A9F9D")) +
  scale_y_continuous(labels = WJSmisc::prob_label, limits = c(0, 1)) +
  theme_minimal(base_family = "serif", base_size = 15) +
  theme(legend.position = "none") +
  labs(title = "Proportion of Students Pursuing \nSome Type of
Postsecondary Education") +
  theme(plot.title = element_text(
    size = 15,
    hjust = 0.5,
    color = "gray20",
    face = "bold"
  ))
```

Coding for Figure 14

The following code was used to create Figure 14: Upward Bound Math and Science Students by PSE Cohort Year, 2016–2021.

```
d_ubms <- read_csv("anonymizedUBandUBMS.csv") %>%
  filter(Type == 2) %>%
  filter(!(PSECohort %in% c("8888", "9999"))) %>%
  distinct(id, .keep_all = TRUE)

d_ubms %>%
  select(Type, PSECohort) %>%
  group_by(Type, PSECohort) %>%
  count %>%
  mutate(PSECohort = factor(PSECohort),
         Type = factor(Type, labels = c("UBMS"), levels = c(2))) %>%
  ggplot(aes(PSECohort, n, fill = Type)) +
  geom_col(position = position_dodge()) +
  theme_minimal() +
  scale_y_continuous(limits = c(0, 35)) +
  scale_fill_manual(values = "#6C8645") +
  geom_text(
    aes(label = n),
    size = 3,
    vjust = 0.5,
    hjust = -0.4,
    label.color = "NA"
  ) +
  theme(axis.title = element_text(size = 9)) +
```

```
  coord_flip() +
  theme(legend.title = element_blank(), legend.position = "none")
```

Coding for Figure 15

The following code was used to create Figure 15: Upward Bound Math and Science PSE Cohorts At a Glance, 2016–2021.

```
d <- modelfit %>%
  mutate(
    race_american_indian = factor(
      Race1,
      levels = c(1, 2),
      labels = c("American-Indian", NA)
    ),
    race_asian = factor(Race2, levels = c(1, 2), labels = c("Asian", NA)),
    race_black = factor(Race3, levels = c(1, 2), labels = c("Black", NA)),
    race_white = factor(Race4, levels = c(1, 2), labels = c("White", NA)),
    race_hawaiian = factor(
      Race5,
      levels = c(1, 2),
      labels = c("Hawaiian/Pacific Islander", NA)
    ),
    ethnic_hisp = factor(
      Ethnic,
      levels = c(1, 2),
      labels = c("Hispanic", NA)
    )
  ) %>%
  unite(
    Race,
    ethnic_hisp,
    race_american_indian,
    race_asian,
    race_black,
    race_white,
    race_hawaiian,
    sep = ", ",
    na.rm = TRUE
  )
bind_rows(
  d %>%
    count(Race) %>%
    mutate(
      variable = "Race",
      Category = fct_reorder(Race, n) %>%
        fct_rev() %>%
        fct_other(drop = "") %>%
        fct_rev()
    ) %>%
    arrange(Category),
  d %>%
    count(GenderCD) %>%
    mutate(
      variable = "Gender",
      Category = factor(
        GenderCD,
        levels = c(1, 2),
        labels = c("Male", "Female")
```

```
      ) %>% fct_reorder(n)
    ) %>%
    arrange(Category),
  d %>%
    filter(!(EligibilityCD == 0)) %>%
    count(EligibilityCD) %>%
    mutate(
      variable = "Eligibility",
      Category = factor(
        EligibilityCD,
        levels = c(2, 3, 4, 1, 5, 6, 7),
        labels = c(
          "Low-income only",
          "First-generation only",
          "At risk for academic failure only",
          "Low-income and first-generation",
          "Low-income and at high risk for academic failure",
          "First generation and at high risk for academic failure",
          "Low-income, first-generation, and at high risk for academic"
        )
      )
    ),
  d %>%
    count(EnterGradeLV) %>%
    mutate(variable = "Grade Level", Category = factor(EnterGradeLV))
) %>%
  select(-Race, -GenderCD, -EnterGradeLV, -EligibilityCD) %>%
  mutate(variable = fct_inorder(variable)) %>%
  ggplot(aes(n, Category)) +
  geom_col(aes(fill = variable)) +
  geom_richtext(
    aes(label = n),
    family = "serif",
    size = 16 * 0.8 / 2.845276,
    label.padding = margin(0.5, 0.5, 0.5, 0.5),
    label.margin = margin(l = 2),
    vjust = 0.5,
    hjust = 0,
    color = "gray40",
    label.color = "NA"
  ) +
  facet_wrap(vars(variable),
             scales = "free",
             nrow = 2,
             ncol = 2) +
  scale_y_discrete(NULL, labels = \(x) str_wrap(x, width = 30)) +
  scale_x_continuous("Count", expand = expansion(mult = c(0, 0.25))) +
  scale_fill_manual(values = c("#CEB175", "#0A9F9D", "#E54E21", "#6C8645"))
+
  theme_minimal(base_family = "serif", base_size = 13) +
  theme(
    plot.title = element_text(hjust = 0.5, face = "bold"),
    strip.text = element_text(
      face = "bold",
      color = "gray30",
      size = 11
    ),
    legend.position = "none"
  )
```

Coding for Figure 19

The following code was used to create Figure 19: Beeswarm Plot: Students' Entering Grade Level and Their Attainment of a Rigorous Course of Study.

```
d_modelfit %>%
  filter(!is.na(RigorousStudy),!is.na(EnterGradeLV)) %>%
  mutate(RigorousStudy = factor(RigorousStudy)) %>%
  mutate(EnterGradeLV = factor(EnterGradeLV)) %>%
  ggplot(aes(y = RigorousStudy, x = EnterGradeLV)) +
  ggbeeswarm::geom_quasirandom()
```

Coding for Figure 20

The following code was used to create Figure 20: Community Service by Participation Status and Year.

```
library(tidyverse)

anonymizedUBandUBMSb %>%
  filter(Type == 2) %>%
  filter(!(PSECohort %in% c(2008:2015))) %>%
  select(id, CmtySer, year, PSECohort) %>%
  mutate(communityservice = case_when(CmtySer == 1 ~ 1,
                                      CmtySer == 2 ~ 0,
                                      TRUE ~ NA_real_)) %>%
  mutate(
    PSECohort = ifelse(PSECohort == "8888", NA, PSECohort),
    possibleyear = ifelse(is.na(communityservice), 0, 1)
  ) %>%
  #filter(PSECohort==2020)
  mutate(CmtySer = factor(
    CmtySer,
    labels = c("Unknown", "Yes", "No", "NA"),
    levels = c(0, 1, 2, 9)
  )) %>%
  summarise(n = n(), .by = c(CmtySer, year)) %>%
  ggplot(aes(year, n)) +
  geom_col(aes(fill = CmtySer)) +
  scale_fill_manual(values = wesanderson::wes_palette(name =
"AsteroidCity1")) +
  facet_wrap(vars(CmtySer))
```

APPENDIX B

R CODE SUPPORTING SELECT TABLES AND FIGURE 18

Included in Appendix B are coding and results that are related to select tables and Figure 18.

Coding for Table 12

The following code was used to create results for Table 12: Correlation Matrix for UBMS Study.

```
library(tidyverse)

rpathanalysis <-
  d_modelfit %>%
  select(
    proportion_communityservice,
    AffilTime,
    AdvancedMath,
    proportion_employment,
    proportion_partlevel,
    EnterGradeLV,
    RigorousStudy
  ) %>%
  mutate(AffilTime = as.numeric(AffilTime)) %>%
  cor(use = "pair")
WJSmisc::cor_heat(rpathanalysis)

rpathanalysis %>%
  round(2)

library(corrr)

rpathanalysis %>%
  as_cordf() %>%
  shave(upper = FALSE) %>%
  mutate(across(where(is.numeric), .fn = WJSmisc::prob_label)) %>%
  mutate(across(everything(), .fn = \(x) ifelse(is.na(x), "", x))) %>%
  kableExtra::kbl(align = "lrrrrrrr") %>%
  kableExtra::kable_paper()
```

Coding for Tables 9, 10, 11, and Figure 18

The following code was used to create results for Tables 9, 10, 11, and Figure 18. All of these relate to the interpretation of path analysis results.

```
library(tidyverse)
library(lavaan)

anonymizedUBandUBMSb <- read_csv("anonymizedUBandUBMSb.csv")
```

```
d_partlevel <- anonymizedUBandUBMSb %>%
  filter(Type == 2) %>%
  #filter(!(PSECohort %in% c(2008:2015))) %>%
  select(id, PartLV, year, PSECohort) %>%
  mutate(
    partlevel = case_when(
      PartLV == 1 ~ 5,
      PartLV == 2 ~ 4,
      PartLV == 3 ~ 3,
      PartLV == 4 ~ 2,
      PartLV == 5 ~ 1,
      TRUE ~ NA_real_
    )
  ) %>%
  mutate(
    PSECohort = ifelse(PSECohort == "8888", NA, PSECohort),
    b_possibleyear = ifelse(is.na(partlevel), 0, 1)
  ) %>%

  summarise(
    PSECohort = mean(PSECohort, na.rm = TRUE),
    proportion_partlevel = mean(partlevel, na.rm = TRUE),
    years_partlevel = sum(partlevel, na.rm = TRUE),
    possible_years_partlevel = sum(b_possibleyear, na.rm = TRUE),
    .by = id
  ) %>%
  filter(!(is.nan(proportion_partlevel))) %>%
  filter(PSECohort != 9999) %>%
  select(-PSECohort)

d_employment <- anonymizedUBandUBMSb %>%
  filter(Type == 2) %>%
  #filter(!(PSECohort %in% c(2008:2015))) %>%
  select(id, Employ, year, PSECohort) %>%
  mutate(employment = case_when(Employ == 1 ~ 1,
                                Employ == 2 ~ 1,
                                Employ == 3 ~ 0,
                                TRUE ~ NA_real_)) %>%
  mutate(
    PSECohort = ifelse(PSECohort == "8888", NA, PSECohort),
    a_possibleyear = ifelse(is.na(employment), 0, 1)
  ) %>%

  summarise(
    PSECohort = mean(PSECohort, na.rm = TRUE),
    proportion_employment = mean(employment, na.rm = TRUE),
    years_employment = sum(employment, na.rm = TRUE),
    possible_years_employment = sum(a_possibleyear, na.rm = TRUE),
    .by = id
  ) %>%
  filter(!(is.nan(proportion_employment))) %>%
  filter(PSECohort != 9999) %>%
  select(-PSECohort)

d_communityservice <- anonymizedUBandUBMSb %>%
  filter(Type == 2) %>%
  #filter(!(PSECohort %in% c(2008:2015))) %>%
  select(id, CmtySer, year, PSECohort) %>%
  mutate(communityservice = case_when(CmtySer == 1 ~ 1,
```

```
                                    CmtySer == 2 ~ 0,
                                    TRUE ~ NA_real_)) %>%
  mutate(
    PSECohort = ifelse(PSECohort == "8888", NA, PSECohort),
    possibleyear = ifelse(is.na(communityservice), 0, 1)
  ) %>%

  summarise(
    PSECohort = mean(PSECohort, na.rm = TRUE),
    proportion_communityservice = mean(communityservice, na.rm = TRUE),
    years_communityservice = sum(communityservice, na.rm = TRUE),
    possible_years_communityservice = sum(possibleyear, na.rm = TRUE),
    .by = id
  ) %>%
  filter(!(is.nan(proportion_communityservice))) %>%
  filter(PSECohort != 9999) %>%
  select(-PSECohort)

anonymizedUBandUBMSb %>%
  filter(Type == 2) %>%
  filter(!(PSECohort %in% c("8888", "9999", 2019, 2020))) %>%
  distinct(id, .keep_all = TRUE) %>%
  select(CultAct,
         PartLV,
         EnterGradeLV,
         Employ,
         AdvancedMath,
         PSECohort,
         RigorousStudy) %>%
  pivot_longer(everything(), names_to = "variable", values_to =
"old_value") %>%
  arrange(variable, old_value) %>%
  write_csv("data_dictionary_raw.csv")

d_data_dictionary <- read_csv("data_dictionary1.csv")

d_modelfit <- anonymizedUBandUBMSb %>%
  filter(Type == 2) %>%
  filter(!(PSECohort %in% c("8888", "9999", 2019, 2020))) %>%
  distinct(id, .keep_all = TRUE) %>%
  pivot_longer(all_of(unique(d_data_dictionary$variable)), names_to =
"variable", values_to = "old_value") %>%
  filter(!is.na(old_value)) %>%
  left_join(d_data_dictionary, by = join_by(variable, old_value)) %>%
  select(-old_value) %>%
  pivot_wider(names_from = variable, values_from = new_value) %>%
  select(id,
         EnterGradeLV,
         PSECohort,
         all_of(unique(d_data_dictionary$variable)),
         ProjEntryDT,
         LastSerDT) %>%
  mutate(
    ProjEntryDT = lubridate::as_date(ProjEntryDT),
    LastSerDT = lubridate::as_date(LastSerDT)
  ) %>%
  mutate(AffilTime = LastSerDT - ProjEntryDT) %>%
  select(-CmtySer, -LastSerDT,-ProjEntryDT, -CultAct) %>%
  left_join(d_employment, by = join_by(id)) %>%
  left_join(d_communityservice, by = join_by(id)) %>%
```

```
  left_join(d_partlevel, by = join_by(id))

# Specify model
specmod <- "
AdvancedMath ~ a*EnterGradeLV
AdvancedMath ~ c*proportion_employment
AdvancedMath ~ e*proportion_communityservice
AdvancedMath ~ g*proportion_partlevel
AdvancedMath ~ i*AffilTime
proportion_employment ~ b*EnterGradeLV
proportion_communityservice ~ d*EnterGradeLV
proportion_partlevel ~ f*EnterGradeLV
AffilTime ~ h*EnterGradeLV
RigorousStudy ~ n*EnterGradeLV
RigorousStudy ~ j*proportion_employment
RigorousStudy ~ k*proportion_communityservice
RigorousStudy ~ l*proportion_partlevel
RigorousStudy ~ m*AffilTime
AdvancedMath ~~ RigorousStudy

bc := b*c
de := d*e
fg := f*g
hi := h*i
bj := b*j
dk := d*k
fl := f*l
hm := h*m
"
set.seed(2023)

fitmod2 <-
  sem(specmod,
      data = d_modelfit,
      se = "bootstrap",
      bootstrap = 5000)

summary(fitmod2, fit.measures = TRUE, rsquare = TRUE)

summary(fitmod2, standardized = TRUE, fit.measures = TRUE)

parameterEstimates(
  fitmod2,
  standardized = TRUE,
  ci = TRUE,
  level = 0.95,
  boot.ci.type = "perc"
)

# Summarize results
summary(fitmod2, fit.measures = TRUE)
```

Results Supporting Tables 9, 10, 11, and Figure 18

```
lavaan 0.6.16 ended normally after 29 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        21
```

```
                                                  Used       Total
  Number of observations                            65         236

Model Test User Model:

  Test statistic                                10.024
  Degrees of freedom                                 6
  P-value (Chi-square)                           0.124

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.911
  Tucker-Lewis Index (TLI)                       0.690

Root Mean Square Error of Approximation:

  RMSEA                                          0.102

Standardized Root Mean Square Residual:

  SRMR                                           0.069

Parameter Estimates:

  Standard errors                            Bootstrap
  Number of requested bootstrap draws             5000
  Number of successful bootstrap draws            4993

Covariances:
                   Estimate   Std.Err   z-value  P(>|z|)
 .AdvancedMath ~~
   .RigorousStudy      0.012     0.017    0.679    0.497
```

```
> parameterEstimates(fitmod2, standardized = TRUE, ci=TRUE, level=0.95, boot.ci.type="perc")
                         lhs op                         rhs label       est        se      z pvalue
1               AdvancedMath  ~                EnterGradeLV     a     0.037     0.125  0.294  0.769
2               AdvancedMath  ~       proportion_employment     c     0.216     0.134  1.607  0.108
3               AdvancedMath  ~ proportion_communityservice     e    -0.581     0.188 -3.091  0.002
4               AdvancedMath  ~        proportion_partlevel     g     0.008     0.079  0.101  0.919
5               AdvancedMath  ~                   AffilTime     i     0.000     0.000  0.720  0.471
6      proportion_employment  ~                EnterGradeLV     b    -0.003     0.073 -0.040  0.968
7  proportion_communityservice  ~              EnterGradeLV     d    -0.054     0.044 -1.240  0.215
8       proportion_partlevel  ~                EnterGradeLV     f     0.130     0.120  1.086  0.278
9                  AffilTime  ~                EnterGradeLV     h  -215.792    52.134 -4.139  0.000
10             RigorousStudy  ~                EnterGradeLV     n     0.222     0.076  2.910  0.004
11             RigorousStudy  ~       proportion_employment     j     0.059     0.100  0.583  0.560
12             RigorousStudy  ~ proportion_communityservice     k    -0.204     0.178 -1.145  0.252
13             RigorousStudy  ~        proportion_partlevel     l     0.136     0.094  1.452  0.147
14             RigorousStudy  ~                   AffilTime     m     0.000     0.000 -1.297  0.195
15              AdvancedMath ~~               RigorousStudy           0.012     0.017  0.679  0.497
16              AdvancedMath ~~                AdvancedMath           0.187     0.018 10.254  0.000
17     proportion_employment ~~       proportion_employment           0.153     0.026  5.835  0.000
18 proportion_communityservice ~~ proportion_communityservice         0.069     0.022  3.218  0.001
19      proportion_partlevel ~~        proportion_partlevel           0.541     0.163  3.326  0.001
20                 AffilTime ~~                   AffilTime       49200.217 13370.331  3.680  0.000
21             RigorousStudy ~~               RigorousStudy           0.094     0.017  5.434  0.000
22              EnterGradeLV ~~                EnterGradeLV           0.336     0.000     NA     NA
23                        bc :=                         b*c    bc    -0.001     0.019 -0.033  0.974
24                        de :=                         d*e    de     0.032     0.027  1.187  0.235
25                        fg :=                         f*g    fg     0.001     0.017  0.062  0.951
26                        hi :=                         h*i    hi    -0.044     0.065 -0.678  0.498
27                        bj :=                         b*j    bj     0.000     0.008 -0.022  0.983
28                        dk :=                         d*k    dk     0.011     0.013  0.838  0.402
29                        fl :=                         f*l    fl     0.018     0.029  0.604  0.546
30                        hm :=                         h*m    hm     0.052     0.046  1.134  0.257

   ci.lower  ci.upper    std.lv std.al
1    -0.229     0.260     0.037  0.045
2    -0.056     0.473     0.216  0.180
3    -1.050    -0.283    -0.581 -0.328
4    -0.098     0.214     0.008  0.013
```

5	0.000	0.001	0.000	0.111
6	-0.142	0.150	-0.003	-0.004
7	-0.156	0.016	-0.054	-0.119
8	-0.104	0.375	0.130	0.102
9	-324.220	-117.258	-215.792	-0.491
10	0.080	0.377	0.222	0.342
11	-0.145	0.248	0.059	0.061
12	-0.709	-0.007	-0.204	-0.144
13	0.046	0.414	0.136	0.268
14	-0.001	0.000	0.000	-0.165
15	-0.023	0.045	0.012	0.090
16	0.132	0.203	0.187	0.851
17	0.094	0.195	0.153	1.000
18	0.027	0.111	0.069	0.986
19	0.235	0.871	0.541	0.990
20	26357.994	76996.033	49200.217	0.759
21	0.052	0.119	0.094	0.666
22	0.336	0.336	0.336	1.000
23	-0.031	0.050	-0.001	-0.001
24	-0.011	0.095	0.032	0.039
25	-0.016	0.052	0.001	0.001
26	-0.151	0.118	-0.044	-0.054
27	-0.014	0.021	0.000	0.000
28	-0.006	0.045	0.011	0.017
29	-0.010	0.105	0.018	0.027
30	-0.039	0.154	0.052	0.081

APPENDIX C

EMAIL REGARDING FIGURES 21 AND 22

From: Christophe Barroche <admin@presentationgo.com>
Sent: 26 January 2024 12:58
To: Bernard L. Dillard

Subject: [External] Re: PresentationGo template in dissertation

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