TIMELY INFORMATION AND STEM PIPELINE OUTCOMES

by

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(Under the Direction of Robert Toutkoushian)

ABSTRACT

An important strand of the STEM pipeline literature stresses students' early educational years as being crucial in terms of developing positive attitudes and affinity toward STEM coursework and careers. Furthermore, by exposing students early on to the nature and requirements of STEM coursework, they may be better prepared to follow a course trajectory that allows them to take advanced mathematics courses in high school. To investigate this notion, I take advantage of a distinct dataset from New Hampshire that surveyed high school seniors about their postsecondary aspirations and important events from their early educational careers. In this dissertation, I use probit regression techniques to explore this dataset and ascertain whether very early student and parent conversations about what to do after high school are related to three STEM pipeline outcomes: taking advanced math courses in high school, taking a high number of science courses in high school, and expressing plans to major in a STEM field of study in college. I further examine whether the relationships of the outcomes variables to the timing of conversations, along with other factors in the model, differ by gender. Results indicate that very early (prior to eighth-grade) conversations are significantly and positively associated with taking advanced math courses in high school. Models disaggregated by gender provide mixed support for the idea that males and females have educational experiences that vary so widely that they require separate models for estimation.

INDEX WORDS: timing, postsecondary information, STEM pipeline, advanced math, high school courses

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DEDICATION

For my parents, David and Sheri, in recognition of what it says about the road so far. For my wife, Katie, in recognition of what it means for our lives moving forward.

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As I was closing out my time in the eighth grade, I met with my school counselor to begin the process of registering for classes as a high school freshman. She asked me what I wanted to be when I grew up, and without hesitation I answered, “a history professor.” I have no idea where I got the notion of joining the faculty ranks someday. In fact, I had even less an idea what that entailed. But it was the first time I can remember someone telling me that I would need to eventually earn a PhD. At the time, the term *graduate school* meant nothing to me. Looking back, it seems odd that this type of scenario would become the subject of my current research. Getting to this point has been a long time in the making, and I owe a great deal of gratitude to many people. I cannot thank them all in this space, but I hope the words that follow can offer some sign of my appreciation.

First and foremost, I must thank my family for their years of unwavering support. Although I may not have always known I would one day earn a PhD, I grew up in a home where I knew that a college degree was not optional. As my grandfather, Murray, always used to say, “You can be anything you want to be: a doctor or a lawyer.” It looks like he was right, sort of.

This dissertation would not have been possible without the guidance of those professors that served on my committee and whose instruction shaped my research interests and abilities. My chair, Dr. Rob Toutkoushian, helped build my confidence in pursuing quantitative methods when he knew I had left the world of math a long time before. He provided me my first opportunity to write for publication and generously allowed me to serve as the first author. He has pushed me to be better in my writing and my thinking, and for that I am truly grateful. Dr. Elizabeth DeBray has always encouraged me to consider the policy implications of my work and the opportunities to drive change in education. I will take that motivation with me throughout my career. Dr. Erik Ness is the reason I came to the Institute of Higher Education. From the first conversation we ever had, he assured me that the faculty at the Institute would do whatever they could to ensure my success. He has been true to his word, and his unending patience with me has been a model of how a professor should treat his or her students.

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My years in Athens were some of the best of my life, and I owe much of the thanks for that to the friends I made there. Being between two cohorts, I got to know more people than most have the chance to. Rob Stollberg, Jason Lee, Maggie Parker, Lucia Brajkovic, and Phil Wilkinson in particular provided the perfect mixture of esprit de corps and commiseration that are necessary for any successful PhD experience. And Doug Chadwick, Mike Trivette, and the rest of the Wolfpack helped make sure that I did not leave the University of Georgia without experiencing game day in Athens. It was a

dream come true to attend a university with such a rich athletic tradition. And it was even better to revel in those and the other good times at Treppenhaus.

The final two years of my graduate school experience included many changes for me, including the start of a new career. Though finding a work-life balance that allowed me to complete my dissertation was a challenge, I always found the support I needed from my AdvancED family. Dr. Vicki Denmark was always open to me taking a day off to return to Athens and encouraged my progress every step of the way. Dr. Veronica Harts and Osiris Jolayemi kept me motivated whenever I was bogged down. Dr. Mike McGill never ceased to regale me with horror stories of his own defense but was equally willing to listen patiently to my statistical wanderings, as was Dr. Matt Dawson. Not only am I grateful for the support of these individuals, but I am also blessed to work for a company that has provided financial support to pay my tuition these last three semesters.

Finally, in addition to moving and starting a new career while trying to write a dissertation, I also married my wife Katie. Trying to manage everything that comes with a new job, a new marriage, and new home along with all the other changes has been one of the more challenging undertakings of my life. And I'm sure there were many weeks (and a few months) that Katie was frustrated by my lack of progress toward graduation. However, she never rushed me or pressured me to finish on someone else's schedule. Instead, she encouraged me when I was stressed and allowed me the freedom to complete my work on my own schedule. I hope I can show her the same degree of patience in all aspects of our life together.

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CHAPTER 1

INTRODUCTION

Recent decades have borne witness to a growing clamor for an intense focus on Science, Technology, Engineering, and Math (STEM) education. With roots tracing back to the Space Race and the oft-cited *A Nation at Risk*, advocates of STEM education argue that the United States risks losing its position of global economic leadership if it does not produce an appropriate number of individuals capable of filling the labor positions that require deep knowledge of STEM content and skills (Bozick & Ingles, 2008; Federman, 2007). A recent Executive Report to the President drew attention to the notion that in order to remain globally competitive the United States will need to produce 1 million STEM professionals–in addition to those being produced at the current rate (Olson & Riordan, 2012). These recommendations reflect the tenor of various earlier reports such as the influential *Rising above the Gathering Storm* (2007) compiled by the Committee on Prospering in the Global Economy of the 21st-Century (CPGEC) and other more recent publications such as the National Science Board's (NSB) *Science and Engineering Indicators* (2016), which warn of looming U.S. economic challenges and identifies the STEM fields and disciplines as part of the path to prevention.

One could argue that the United States boasts perhaps the strongest higher education system in the world, certainly capable of meeting the needs of the emerging economy. This simply is not true; in fact, students in the U.S. consistently underperform relative to their peers in other countries, particularly those belonging to the Organization for Economic Co-Operation and Development (OECD). Data from the 2003 Trends in International Mathematics and Science Study (TIMSS), for example, showed that U.S. students were ranked lower in math literacy than peers in 23 other participating OECD countries and four non-OECD countries (Gonzales et al., 2004; Kuenzi, 2008). Based on 2012 Program for International Student Assessment (PISA) data, it appears little progress has been made, with neither male nor female 15-year-old students in the U.S. showing significant improvement in math literacy from 2003 to 2012 (NSB, 2016). These same students also demonstrated math literacy scores that were below the average for all developed countries. Similarly discouraging findings emerged with regard to science knowledge. According to results from the TIMSS:2012, the U.S. leads all other developed countries in producing students performing at or below the 10th percentile. Even after taking into account the size of the U.S. population, 17 percent more students fall into this category when compared to all other developed countries. The U.S. does not make up this ground in the top of the distribution either. On the contrary, as the NSB reports, “the United States produces fewer students above the scores that define the 90th, 95th, and 99th percentiles across all developed countries. The United States has about 23% fewer students in each of these high-score groups” (p. I-36).

Given the economic value tied to producing workers with high-level math and technical skills (Bozick & Ingels, 2008), it is no surprise the U.S. has increased its efforts to produce more STEM graduates. Of course, the rest of the world is not sitting idly by while the United States tries to improve its global economic position. As the National Science Board (2016) explains,

> S&E [science and engineering] degrees, important for an innovative knowledge economy, have become relatively more prevalent in some Asian countries than in the United States: in China, nearly half of all first university degrees (49%) awarded in 2012 were in S&E, compared with 33% in the United States. Globally, the number of first university degrees in S&E reached about 6.4 million, according to the most recent estimates. Almost half of these degrees were conferred in China (23%) and India (23%); another 21% were conferred in the European Union […] (12%) and in the United States (9%). (p. O-4).

What is more, the United States is also not alone in recruiting STEM degree holders. As the world's workers become increasingly more mobile, nations across the globe compete to attract them (Bowen, Chingos, & McPherson, 2009; OECD, 2012).

Findings such as these have led to the policy imperative aimed at improving the educational pipeline[1] that leads to the production of individuals with STEM degrees. As clear as the need seems to be, though, causes and solutions to the problem vary greatly. Research regarding the P-20 pathway toward becoming a STEM professional has considered the role of ability and affinity (Bonous-Hamarth, 2000; Hazari, Tai, & Sadler, 2007; Ware & Lee, 1988); socioeconomic status (Christnensen, Knezek, & Tyler-Wood, 2014; Madigan, 1997; Tai, Sadler, & Loehr, 2005; Trusty, 2002); students' classroom experiences (Ardies, De Maeyer, & Gijbels, 2015; Baker & Leary, 1995; Cleaves, 2005; Maltese & Tai, 2011; Osborne, Simon, & Collins, 2003) and outreach (Blustein et al., 2013; Dell, Christman, & Garrick, 2011; Maple & Stage, 1991; Zhang & Barnett, 2015).

[1] Although the Association for the Study of Higher Education (Museus et al., 2011) and Xie and Schauman, 2003) make a strong case for the use of terms such as *STEM circuit* in lieu of *STEM Pipeline,* in this work I make use of the latter as it is in keeping the majority of the literature on the topic. In essence, the term *STEM Pipeline* refers to the trajectory of students from elementary school to earning STEM degrees and ultimately entering STEM fields.

Complicating all of this research is the repeated finding that, despite all we have learned about this topic, a students' experience in the STEM educational pipeline varies substantially based on that students' race and ethnicity and especially gender. Although Asian students tend to do well if not better than their peers, including white students, African American and Hispanic students demonstrate weaker STEM outcomes and remain underrepresented in STEM fields (Adelman, 2006; Bonous-Hammarth, 2000; Bozick & Ingels, 2008, Madigan, 1997; Museus, Palmer, Davis, & Maramba, 2011; Navarro, Flores & Worthington, 2007).

It seems, though, that the most consistent, or at least most documented, contributing factor to students' STEM outcomes is gender. Countless studies have produced or commented on findings that time and again reveal that females are at a distinct disadvantage as they progress through the STEM pipeline (Baker & Leary, 1995; Barton, Tan, & Rivet, 2008; Corbett, Hill, & St. Rose, 2008; Cordova-Wentling & Camacho, 2006; Dell et al., 2011; Hazari et al., 2007; Hill, Corbett, & St. Rose, 2010; Maple & Stage, 1991; Riegle-Crumb & Moore, 2013; Xie & Schauman, 2003). Fortunately, these myriad studies have improved our knowledge of the plight of females in the STEM pipeline over the past several decades, and in that time, progress has been made. For instance, the National Science Foundation (NSF) reported that since the late 1990s, women have earned nearly 60 percent of all bachelor's degrees and nearly half of science and engineering bachelor's degrees (NSF, 2015). However, these gains in attainment do not directly correlate to the STEM occupational landscape as women comprise half of the total college educated workforce in the U.S. while only making up 29 percent of those employed in science and engineering fields (NSB, 2016). The outlook is even worse for minority women, who account for fewer than 1 in 10 employed scientists and engineers (NSF, 2015).

As researchers have investigated student progression through the STEM pipeline, the role of high school course-taking has emerged as an important topic and has been considered both as an input and an outcome (Ardies et al., 2015; Bonous-Hammarth, 2000; Bozick & Ingels, 2008; Clotfelter, Ladd, & Vigdor, 2013, 2015; Loveless, 2008; Riley, 1997; Tai, Liu, Maltese, & Fan, 2006). The leading argument for focusing on advanced high school coursework, particularly mathematics, relies on findings from studies that have shown strong associations with mathematics training–beginning with Algebra I– and improved postsecondary academic outcomes such as college attendance and graduation, job selectivity, and higher salaries (Achieve Inc., 2008; Bozick & Luaff, 2007; Byun, Irvin & Bell, 2015; NSB, 2016; Gaertner, Kim, DesJardins, & McClarty, 2014; Gamoran & Hannigan, 2000; Long, Conger & Iatarola, 2012; Nord et al., 2011; Trusty, 2002; Tyson et al., 2007; Ware & Lee, 1988). Based on such positive associations, some states and districts have responded by creating policies that force some students into Algebra I classes as early as 8th grade. A few scholars have argued that these types of policies can lead to negative outcomes for students not adequately prepared for these courses (Clotfelter et al., 2015, 2015; Gaertner et al., 2014, Loveless, 2008, 2013). Still, others contend that providing students with advanced math training has become a civil rights and equity issue based on its ability to empower disenfranchised students to participate in an economy that requires those skills (Moses & Cobb, 2002; The Algebra Project, 2016; U.S. Department of Education, 1997; Wilgoren, J. 2001).

Most of these policy conversations and exchanges in the literature, however, concern the time when students are in high school or perhaps the eighth grade, but the reality is that students' STEM-related outcomes may be influenced by factors that occur before then (Barton et al., 2008; Dell et al., 2011; Dozier et al., 1997; Maltese & Tai, 2010, 2011; Tai et al., 2006; Trusty, 2002). Many, for example, consider Algebra I to be a gatekeeper course to later study, which is most beneficial if taken in the eighth grade in order to maximize course-taking options in high school (Atanda, 1999). To the extent that this is true, students would likely benefit by thinking about their eventual plans even earlier. Indeed, prior research has shown that early exposure to information about college is associated with early student decisions to attend college (Harding, Parker, & Toutkoushian, 2017) and that students who decide before middle school to go to college are more likely to apply (Harding et al., 2017) and to enroll (Eccles, Vida, & Barber, 2004). The large national datasets that measure STEM pipeline outcomes only contain information about students as far back as the eighth grade, which has limited our ability to measure how early adolescent factors influence choice of major and degree attainment. However, in this study, I rely on data from New Hampshire that offers a retrospective look on this time in students' lives to consider whether students' very early (prior to the eighth-grade) conversations with parents concerning what to do after high school is in fact associated with later advanced math course taking in high school and/or students' plans to major in a STEM field in college.

Statement of the Problem

Despite having the attention of researchers, policymakers, and educators for several decades now, the lack of sufficient numbers of STEM graduates–from multiple backgrounds–remains an educational and economic concern for the United States. Although many interventions target those students nearest to college matriculation, research indicates that the process leading to an eventual STEM career likely begins early on in childhood. Anecdotal evidence of this can be found scattered among the literature on the topic. By leveraging a unique dataset from New Hampshire, this study takes an important step forward in addressing this resulting gap in the literature. Specifically, in this study I explore the following research questions:

1. How does the timing of students' earliest conversations with parents regarding what to do after high school relate to three important STEM pipeline outcomes: (a) taking advanced mathematics courses, (b) taking more than three years of science, and (c) expressing plans to major in a STEM field of study
2. Do these relationships vary based on gender?

Prior research has investigated students' early life and school exposure to postsecondary information through small-sample, qualitative means, yielding results that suggest early information would lead to more students choosing STEM fields. Large-scale quantitative research has done little to support these findings, however, given the absence of relevant questions and the lack of data that interrogates students' earliest experiences. Even the most current national dataset, the High School Longitudinal Study of 2009 (HSLS:09), which the National Center for Education Statistics (NCES) intended to be a nationally-representative study of students specifically focusing on issues relevant to STEM, fails to capture sufficient information regarding student's experiences before high school. As such, the current study addresses a critical question that existing data sources are ill-equipped to answer and that can have important implications for school policy and practices at local, state, and national levels.

CHAPTER 2

THEORY AND LITERATURE

Theoretical and Conceptual Frameworks

The selection of a college major is often complicated. It begins first with the choice whether to attend college at all. And, hopefully, along the way an individual takes high school courses that build knowledge and skills in areas that will prepare them for the eventual postsecondary work. The literature regarding these topics considers both choice of courses and choice of major from myriad viewpoints and lenses. As such, in this study I draw upon multiple theories from a range of fields to generate research questions, inform the selection of variables, and motivate the necessary analytical approaches.

Human Capital Theory (Becker; 1965, 1993; Mincer, 1958) serves as the primary theory that grounds this study. This theory considers education and experience as a means through which personal non-pecuniary resources can be expanded and refined in order to achieve other meaningful outcomes. Accordingly, an individual may pursue additional years of schooling or more advanced courses in a particular area to enhance her knowledge and abilities so that she might become qualified to perform varying types of work. The educational system has been built in such a way as to scaffold the acquisition of human capital with material in one year ideally leading into the material for the next. In this study the notion of scaffolded human capital formation plays out in a few important ways. First, students desiring to major in a STEM field or discipline must do so in a postsecondary institution. Those who wish to attain some form of postsecondary education must first complete prerequisite coursework in high school.

Similarly, work in mathematics–and to a much lesser extent science–is often sequential. That is, students must first master basic mathematical principles before moving into algebraic expressions and geometry and from there on to trigonometry, pre-calculus and more advanced work such as differential equations. This principal holds true for transitions from high school into postsecondary study. In fact, many programs require–or at the very least prefer–students who demonstrate a progressive trajectory of mathematical study throughout high school ending with advanced work. This is of particular concern in STEM fields.

Beyond these points, Human Capital Theory also posits that not all types of investments garner the same reward. Studying law, for example, leads to greater financial returns, on average, than studying English literature. The same can be said of studying topics related to engineering relative to the fine arts. Under this premise, students who invest in more courses related to STEM fields may be doing so with the hopes of receiving a larger monetary payout in the 21^{st}-century economy. Such an idea is bolstered by increasingly pointed and frequent rhetoric from news and policy outlets that focus on high market demand for STEM professionals predicted in the coming years (Olson & Riordan, 2012; NSB, 2016).

Though Human Capital Theory may explain how individuals may view postsecondary education as an avenue for improving one's situation from a broad economic perspective, the theory by itself cannot adequately explain the decisions involved throughout the entire process. This is in large part because all individuals cannot be thought of as equally equipped to make decisions about their education and their postsecondary futures and careers. Bourdieu (1977, 1986) argues that individuals each possess varying levels of cultural capital that shape values and understanding of these areas. Thus, a student whose parents both possess college degrees will likely have a more developed understanding of not only the possibilities of self-improvement through education, but also the relative returns to the variety of disciplines and degrees. These advantages do not come only through parental differences. Bourdieu also discusses the ways in which exposure to cultural events, such as the theatre and museum visits, also adds to an individual's aggregate cultural capital. Of course, these advantages also arise as a function of wealth, with those having more financial capital also benefitting from corresponding levels of cultural capital (Orr, 2003).

Individuals can augment, or even substitute, their cultural capital by leveraging their social capital (Coleman, 1988). Social capital describes the relationships and connections an individual can leverage to obtain information and guidance. In the college choice paradigm this could be thought of as family members who share knowledge or experience navigating the process of selecting and enrolling in a postsecondary institution. Friends and acquaintances can also serve as valuable sources of social capital. As with most forms of capital, though, access remains a point to consider. Not all individuals have family members or friends who have knowledge of the college choice process, nor do they always have other immediately apparent social connections that can fulfill this role. Often a lack of social capital corresponds with paucities in other forms, leading to compound disadvantages. For many individuals lacking their own networks of social capital, school personnel such as counselors and teachers often must serve the role of informant and guide (Bonous-Hammarth & Allen, 2005; King, 1996; Somers, Cofer, & VanderPutten, 2002). Some groups in particular, such as immigrants, often have to rely heavily on social capital when other aspects of their status (e.g. poverty or residency status) have cut them off from other forms of financial and cultural capital (Stanton-Salazar & Dornbusch, 1995).

The forms of capital thus far can be applied broadly to the idea of choosing courses in high school or deciding to go to college. Other scholarship, however, has considered the process more closely. Most famously, Hossler and Gallager (1987) conceptualized the process as including three distinct phases: predisposition, search, and choice. The predisposition phase has generally been considered to begin early in middle school and refers to a period when individuals develop aspirations for postsecondary education. A students' predisposition toward pursuing a college education is believed to be influenced by a number of individuals, from parents and friends to school counselors and teachers, and by myriad factors from family income to peer effects in grade school.

Students' various reserves of the types of capital discussed above also shape not only whether students become predisposed to attend college but also when they become predisposed. Though most of the college choice literature has traditionally considered middle school to be the time when students first begin forming their ideas and aspirations for college, some research suggests this might begin even earlier into childhood (Eccles et al., 2004; Harding, et al., 2017). In the current study, the timing of students' predisposition for college is of paramount importance as students who begin thinking about college in elementary or middle school may be more likely to follow course paths in high school that better prepare them for pursuing STEM majors in college. That is, a college's engineering program may require students to have taken advanced mathematics and science coursework in high school before being admitted to their department. This would be a difficult criterion to meet if a student only begins to seriously think about college in his or her sophomore or junior year of high school.

As Hossler and Gallagher (1987) propose, once a student has formed those initial ideas about college in the predisposition phase, he or she transitions into the search phase. During this time students gather information about college topics ranging from financial aid to school selectivity. Armed with whatever information they have managed to accumulate, students make a choice about which particular institution they wish to attend. Toutkoushian and Paulsen (2016) have further noted that, at this point, students must still apply to the institution, or a choice set of institutions, and await notification of acceptance. Then, based on what institutions have admitted the student, he or she chooses the most preferred one.

The college choice theory, however, does not adequately address the process of selecting a major area of study. As such, to explain the process of major choice selection, much of the recent literature on the topic has relied on Social Cognitive Career Theory (Lent, Brown, & Hackett, 1994; 2000). In developing Social Cognitive Career Theory (SCCT) Lent et al. (1994) extend the earlier work of Bandura (1986) regarding general social cognitive theory to explain aspects of career development, including the formation of interests, which relates to the current study through its connection to planned postsecondary major. In summary, Lent et al. (1994) state that SCCT "emphasizes three social cognitive mechanisms that seem particularly relevant to career development: (a) self-efficacy beliefs, (b) outcomes expectations, and (c) goal representations" (83). The concept of self-efficacy beliefs refers to an individual's assessment of his or her overall competencies in a particular area. Departing from traditional treatments of self-efficacy as a passive and fixed quality, SCCT considers self-efficacy to be mutable, given to change through interactions with myriad other intrapersonal and contextual factors (Lent et al., 1994). The second component of SCCT, outcomes expectations, refers to an individual's beliefs about the consequences of his or her career decisions. Finally, goals most strongly represent an individual's volition with regards to a career or major choice.

In a follow-up to their seminal (1994) piece, Lent et al. (2000) updated their original development of SCCT by more explicitly acknowledging the role that barriers and challenges play in determining career outcomes. Barriers can be obvious restrictions, such as citizenship challenges preventing immigrant students enrolling in higher education in some areas, as well as less-tangible restrictions such as bias in classrooms. Many researchers have pointed to gaps in STEM field representations for females as evidence of the barriers women face in persisting to–or even developing interest in–careers in those areas. Based on theoretical discussions of these barrier differences between males and females by scholars such as Jacquelyn Eccles (1987), some researchers have argued that analyses in this topical area should consider the pathways of males and females separately when estimating models (Kao & Tienda, 1998; Webber & González Canché, 2015).

Despite decades of research, though, gender gaps persist in many spaces along the STEM pipeline. A such, this topic remains one of the most widely discussed areas of the literature on STEM education. As Blickenstaff (2005) quipped, "A review of every paper written on the topic of gender and STEM would be the work of a lifetime" (p. 371).

Though the focus of the current study concerns the timing of college-related information and students' decisions about college, the decision to estimate separate models for each gender merits some grounding in the literature on STEM outcomes. The feminist school of thought, in particular, has much to say on the topic.

Research conducted from a feminist perspective has argued that girls' experiences in science education often differ greatly from their male peers to the point that everything from subject matter and pedagogy to teacher expectations creates environments that elevate the success of males and dissuade females from pursuing further study in STEM areas (Hazari et al., 2007; Osborne, 2003). As Barton et al. (2008) observe, "We know that traditionally girls are positioned with less power in the science classroom. Girls are called on less often to answer content questions and are not given as much attention as the boys by the teacher" (98). Hazari et al. (2007) use even stronger language to make this argument:

> Science is hegemonic and androcentric, two characteristics that proceed from the fact that practitioners of science as we know it have traditionally been white, male, and Western. It is they who define the rules, methods, instrumentation, descriptions of results, and criteria for knowledge production. It is they who define what counts as science, both theoretically and in practice. It is they who are the gatekeepers for access to, and definers of, a life in science. (p. 604)

Unfortunately, though these appraisals of science may be accurate, it is difficult to provide quantitative support. As such, much of the work exploring this idea tends to be qualitative and/or on a small and non-representative scale. Nevertheless, the feminist interpretation of the biases women face in the STEM pipeline, from early education on into a career, has served as a compelling lens for explaining gender gaps that are unresolved by numerous other explanatory variables in many models.

The process of deciding to attend college and selecting a major area of study to explore once there remains decidedly complex. And though the number of theoretical lenses discussed above may appear excessive, each plays a part in informing the selection of variables, the specification of models, and the overall analytic approach used to investigate this complicated process. The subsequent section of this chapter reviews the ways in which various authors have drawn upon these theories to explore problems similar to those considered by the research questions I pose in the current study.

Review of the Literature

College choice literature. Any discussion regarding students' choice of college major is moot without first at least briefly mentioning the process students follow in determining whether to even go to college at all. Although an in-depth review of that literature is not appropriate for the current study, an overview of some of its larger themes is both relevant and instructive as many journal articles and book chapters are guided by the same theories and principles that motivate the selection of variables and analytic approach found herein. Indeed, though few studies directly link college-choice and selection of major, in many respects they go hand-in-hand.

As mentioned above, the dominant framework of analysis in the college choice literature remains the three-stage model of predisposition, search, and choice developed by Hossler and Gallagher (1987). Despite a common adherence to this structure, though, researchers have regularly invoked myriad theories and lenses for applying it. Some studies have focused on the influence of demographic variables such as gender (Mau &

Bikos, 2000) and race and ethnicity (Engberg & Wolniak, 2009; Freeman, 1997; Hamrick & Stage, 1998; Hurtado, Inkelas, Briggs, & Rhee, 1997; Perna & Titus, 2005; St. John, 1991). In general, research has shown that, compared to males, females tend to have higher educational aspiration levels and are more likely to enroll in college whereas African-Americans, Hispanics, and Native Americans face additional hurdles and remain underrepresented in postsecondary education (Perna, 2000; Perna & Titus 2005). Asian students, on the other hand, express higher levels of college aspirations than other racial and ethnic groups, even whites (Kao & Tienda, 1998), and are more likely to enroll in college (Hsin & Xie, 2014), especially at their first choice (Hurtado, Inkelas, Briggs, & Rhee, 1997).

Others have considered the influence of factors related to college affordability. The foundation of these studies often centers on students' socioeconomic status (Cameron & Heckman, 2001; Carter, 1999; Plank & Jordan, 2001) with findings almost always indicating the advantages experienced by those students who come from families of greater means. Of course, the issue of affordability is not simply a matter of family wealth and income. Students' perceptions of affordability can also play a role as some students believe the costs of college far exceed what they would actually be required to pay (George-Jackson & Gast, 2015). In other cases, students may be aware of costs but have limited information about or differential access to financial aid (Cameron & Heckman, 2001; Flint, 1993; Perna & Steele, 2011; St. John, 1991).

STEM pipeline literature. Having provided a brief overview of studies related to the college choice process, I now turn to the literature more specifically focused on the STEM pipeline. In many cases, the two bodies of literature draw upon the same constructs and control factors such as personal and background demographics. Studies on the STEM pipeline differ, however, in that many important factors considered by researchers are more specifically tied to the four content areas of science, technology, engineering, and mathematics. Because STEM pipeline studies have considered so many variables which serve as outcomes in some instances and predictors in other, depending on the stage of the pipeline, logically summarizing the existing research can be problematic. Blickenstaff (2005) echoed this sentiment, explaining, “One of the significant challenges when looking at the literature on girls or women in science is devising a way to organize the very disparate subtopics into meaningful categories” (p. 370). And he was only referring to the literature on women and science. In this study, I have found it most manageable to present a review of the literature organized by particular variables or groups of variables and, when needed, explain which side of the equals sign they occupied in a given work. The resulting review begins with a discussion of the role of advanced math and science course taking, which serves as the outcome variable (taking advanced mathematics courses) in the first part of my analysis and a predictor variable in the second.

Number and type of science and math courses. In stressing a quality education as the means to ensure that our nation’s students can compete in the emerging global economy, the National Science Board (2016) specifically pointed to the importance of taking advanced math and science courses, and for good reason. Researchers spanning more than a decade have explored the links between this type of coursework and positive career- and postsecondary-related outcomes (Ardies et al., 2015; Bozick & Ingles, 2008; Horn & Kojaku, 2001; Madigan, 1997; Nord et al., 2011; Rose & Betts, 2004; Tai et al., 2005). Gamoran and Hannigan (2000) performed least squares regressions in their analysis of NELS data and concluded that, net of background factors and prior ability, taking algebra in eighth, ninth, or tenth grade was associated with significantly higher math achievement growth of as much of a third of a standard deviation compared to those who had taken no algebra at all. Although results indicated that, regardless of ability level, all students benefit from taking algebra, the effects were found to be somewhat smaller for those whose eighth-grade math tests were in the bottom 20^{th} percentile.

Altonji (1995) presented one of the earliest efforts at using quasi-experimental approaches to link course-taking with postsecondary outcomes, and his results, to some extent, supported the typical human capital argument. Employing variation across schools related to what courses students take as an instrument for the actual curriculum, Altonji found that, among students participating in the National Longitudinal Survey of the High School Class of 1972 (NLS72), an additional year of high school science, math, and foreign language only led to a .017 increase in wage growth rate. Similarly surprising to the author, the same curricular increase was also only associated with an additional .339 years of postsecondary education. Altonji pointed to less-than-desirable controls for ability in the NLS:72 data as one possible explanation for the surprisingly low estimates to the returns on math, science, and foreign language courses in the study. Rose and Betts (2004) later extended Altonji's (1995) work using a slightly modified version of his instrumental variables approach and examining more recent High School and Beyond (HSB) data. Although they did establish connections between additional high school math coursework and higher career earnings, the effects were concentrated mostly in algebra and geometry courses.

In another related study, Levine and Zimmerman (1995) employed both ordinary least squares (OLS) regression and an instrumental variables to estimate the returns to math and science coursework in high school, both in terms of effects on wages and educational outcomes. Based on data from the National Longitudinal Survey of Youth and HSB, estimated models using both analytic approaches revealed that women who took additional math courses in high school and went on to graduate college eventually earned increased wages (2.9 and 5.4 percent increases in NLSY and HSB, respectively). Among female college graduates in the HSB sample, taking an extra half-year of math in high school increased an individual's probability of majoring in a technical field by three percentage points. The increased mathematics coursework also led to a near three percentage point decrease in an individual's probability of majoring in a field traditionally dominated by women. Similar findings arose from the models using NLSY data; however, the magnitude of the effects were slightly smaller. Levine and Zimmerman closed their study by urging caution with interpreting the results as the instruments employed in the study were fairly weak, leading to much larger standard errors than those seen in the traditional OLS models.

Federman (2007) followed this quasi-experimental line of inquiry by investigating the influence of high school course taking on students' decisions to major in a technical field. Relying on NELS data, the author first used students' total math and science courses to predict their probability of majoring in a technical field, net of other relevant controls. Findings from these models suggested that all else equal, at the means, an extra year of math and science course-taking for a student should lead to a six percentage point increase in a male's probability of selecting a technical major and nearly half that for a female. When Federman used state graduation requirements related to math and science courses as an instrument for total number of courses, the coefficients of interest were nearly twice as large. Of course, the NELS data related to a time when math requirements at the state level tended to be either two or three years. Thus, while it would stand to reason that a four-year requirement would have similar effects, Federman's (2007) study could not corroborate such a theory.

Joensen and Nielsen (2009) similarly provided positive results for the returns to mathematics coursework but in an international context. Taking advantage of data from a natural experiment in Denmark, the authors used an instrumental variables approach to measure the labor market returns to high school advanced math. The identification strategy the authors chose led them to assert a near causal connection between the two, pointing out that students taking advanced math in high school could expect a 20 percent increase in earnings relative to an average student that had not taken advanced math. It is worth noting that this effect pertained to the treatment condition of choosing an advanced math and chemistry branch. However, the authors cited prior literature that supported the notion that labor market returns are much more closely tied to math education than science education.

Returning to the U.S. education landscape, Gaernter et al. (2014) continued the instrumental variables approach to investigating the returns to studying math, using NELS and ELS to compare the returns to taking Algebra 2 during two different timespans– 1988 to 2000 and 2002-2006, respectively. In sum, the authors found that taking Algebra II in high school has positive effects on college outcomes (i.e., first-year retention and graduation) after accounting for potential self-selection bias, but this effect was attenuated between the NELS and ELS time periods. It is worth noting that the authors of this study also considered whether taking Algebra II in high school led to similarly positive outcomes for those seeking a career immediately after high school and determined that this was not the case. As such, the authors suggested there may be opportunity costs for career-seeking students who are pushed or required to take Algebra II in high school.

Most recently, Byun et al. (2015) analyzed ELS (2002-2006) data to analyze the effects of advanced math course taking on math achievement and college enrollment. Results from models that leveraged propensity score matching revealed that advanced mathematics course taking led to an increase of nearly nine points on the 12th grade mathematics achievement test. Interactions also revealed that achievement gains were greater for lower SES students but lower for Black students. Students who took advanced math courses in high school were also two times more likely, on average, to enroll in college. Although advanced math takers in the matched samples were slightly more likely to experience increased enrollment in the two-year sector (compared to no enrollment), the larger benefit was seen for those enrolling in the four-year sector.

Ability, affinity, and personal taste. Before the development of the term *STEM* truly entered mainstream discussion, researchers had already begun considering ability as an important predictor of science and math related outcomes such as college major, degree type, or career. These factors played particularly important roles in the literature concerning differences in outcomes between males and females (Blickenstaff, 2005). Of course, in the earliest iterations of this research, a deficit orientation prevailed (Eccles, 1987), leading to explorations of whether biological and physiological factors such as arm length, brain size, and field dependency could explain differences in ability-related outcomes (Blickenstaff, 2005). In more recent literature, ability has been considered as one of many controlling factors as opposed to a primary predictor of interest (Navarro et al, 2007; Nicholls, Wolfe, Besterfield-Sacre, and Shuman, 2010; Nicholls, Wolfe, Besterfield-Sacre, Shuman, & Larpkiattaworn, 2007; Tai et al., 2006;).

This is not to say ability does not matter in predicting STEM outcomes, only that its relationship has already been well established. For example, Bonous-Hammarth (2000) explored a combination of Cooperative Institutional Research Program (CIRP) and Integrated Postsecondary Education Data System (IPEDS) data from the 1980s, which revealed that high academic achievement was positively associated with persistence in science, math, and engineering undergraduate work, including underrepresented minorities (African-American, American-Indian, and Chicano/Latino). Nicholls et al. (2007), supported this finding, showing that academic ability was one of the most important variables in predicting students' plans to major in STEM when using samples from more recent (2000s) CIRP data. In a later study, Nicholls et al. (2010) arrived at similar findings using National Education Longitudinal Study (NELS) data, which corroborated earlier work by authors such as Federman (2007), who used NELS data to demonstrate the positive connection between academic achievement in middle and high school and majoring in technical field in college. Students' own perception of their ability, what Bandura (1986) and Lent et al. (1994, 2000) refer to as *self-efficacy*, has also been shown to be important in this line of research (Navarro et al., 2007; Zhang & Barnett, 2015), as students that see their science and mathematics ability as areas of personal strength are often more likely to take advanced math courses in high school (Simpkins, Davis-Kean, & Eccles, 2006) and pursue STEM careers (Trusty, 2002).

The idea of ability has been particularly important with regards to gender. As researchers began to empirically affirm casual observations of differences in STEM outcomes for males and females, many scholars quickly turned to the idea of natural ability differences between the sexes. Early studies considered the role of biology and investigated the role of physiological variables such as brain size and chemistry to discover what, if any, differences naturally existed between the intellectual capabilities of men and women (Blickenstaff, 2005; Ceci et al., 2005; Hill et al., 2010). Limited but contested evidence related to field dependency seemed to support the notion that males might be more naturally and favorably predisposed to excel in math and the sciences (Blickenstaff, 2005); however, findings in this area became uninformative as thinking about the issue evolved. Eventually these comparisons ceased to play a prominent role in the literature. Nevertheless, studies do still uncover differing influences for some ability-related variables. Relying on NELS data, Trusty (2002) showed that better early performance in math among females led to subsequent increases in the likelihood of taking advanced math courses, which in turn led to higher probabilities of majoring in a science or math field. Federman (2007) similarly found that whereas higher math scores did not predict a higher probability of majoring in a technical field for males, the relationship was positive and significant for females.

A related construct often used in STEM pipeline research accounts for the importance of students' affinity for science and mathematics courses and their belief in each field's value (Christensen et al., 2014; Osborne et al., 2003; Nicholls et al., 2010, Simpkins et al., 2006; Ware & Lee. 1988). A study of 437 sixth grade students (Jones, Howe, & Rua, 2000), for example, revealed that whereas males saw future science jobs as a means to become famous, earn money, and control other people, females, on the other hand, saw science jobs as a way to "help other people" (p. 186). Affinity for and perceived value of STEM subjects continue to matter as students age. Using High School and Beyond (HS&B) data, Ware and Lee (1988) found that positive attitudes toward mathematics in high school are an indirect but important predictor of students' choice of a science major in college. Bell (2001) suggested that differences in personal taste might account for the significant differences he found in performance on recall-based science questions on which boys outperformed girls on physics-related items and girls outpaced boys on those related to human biology. In more recent work involving 1531 students at 12 different, but unnamed, colleges and universities in the U.S., Tai et al. (2005) reported that, on average, students who entered science as a means to a better career earned grades in introductory college chemistry that were about ten percent better than their peers. Indicators of attitudes have often been problematic in STEM research, however. As Osborne et al. (2003) noted, the existing literature commonly uncovers contradictions between students' attitudes toward school in general and science specifically, with many students enjoying the latter while objecting to the former. Additionally, student personal attitudes for science (and math) likely often lead to issues of self-selection bias in studies concerning outcomes such as choice of STEM major (Federman, 2007).

Classroom experience. Though ability and affinity for STEM coursework has been linked to STEM outcomes, the influence of these factors may be mitigated by students' experiences in their STEM classes (Ardies et al., 2015; Osborne et al., 2003).

Osborne et al. (2003) note that the STEM literature consistently calls on educators to make science teaching engaging for students, especially since the reliance on note-taking, lectures, and textbooks begins to increase as early as the eighth grade (Baker & Leary, 1995). The resulting teaching and learning environments can be detrimental to student success. Determining which environments are best can be complicated, however. Osborne et al. (2003) reviewed this literature and concluded that chemistry classes that depart from lab-oriented practices, such as manipulating chemicals, shift too far from the practical and move to the theoretical, making it difficult for many students to perceive the relevance of the material to their daily lives. Tai et al. (2005) found that students whose high school chemistry classes had overemphasized lab procedures tended to perform more poorly in their introductory college chemistry courses. Those individuals whose high school chemistry classes featured labs repeated for understanding, however, tended to perform better in college. Similarly, results from Maltese & Tai's (2011) study using NELS:88 data revealed that students whose experiences in mathematics classes involved a heavy focus on learning facts and rules were less likely to eventually earn a STEM degree.

As with ability and affinity, the influence of classroom experience also remains an area of the literature in which researchers strongly consider the interacting effects of gender. In large part, this discussion has focused on longstanding issues of equity in the classroom rather than on differences in student behaviors or abilities (Oakes 1990; Sadker, Sadker, & Klein, 1991). Textbooks, for example, were long shown to be absent of positive female role models, and often even included sex-based stereotypes portraying females as more dependent and passive than males. Even as publishers began to make improvements by portraying females in a wider variety of scientific roles, they still appeared less frequently (Sadker et al., 1991). These biases play out in other seemingly small ways in classrooms as well. As Barton et al. (2008) noted, females are also called upon less frequently in science classes and are not given as much attention by the teacher when compared to their male peers. Classroom activities have similarly been pointed to as affecting males and females differently. Baker and Leary (1995) found that, in their sample, females reacted negatively to pedagogy that isolated them and forced them to work separately. They also expressed aversions to traditional styles of testing. Hazari et al. (2007) observed that content can matter as well. Reporting on results from their study of women in introductory university physics course performance, they explained females benefited from high school physics courses that required a deeper understanding of subject matter. Males, on the other hand, had more success when their high school physics classes involved more rote exercises such as memorization. Of course, despite the relatively recent publication date of the study, the authors relied on data from students enrolled in those courses in 1973. Females begin to notice differences in classrooms early on as well. Females in Riegle-Crumb and Moore's (2013) study of students in a high school engineering class reported perceptions of their classroom as less inclusive after having only been present for a few days at the beginning of the year.

In many cases, the influential factors discussed above are directly tied to decisions made by teachers (Tai et al., 2005). As Kuenzi (2008) stated, "Many observers look to the nation's teaching force as a source of national shortcomings in student math and science achievement" (p. 10). Cordova-Wentling & Camacho (2006), for example, interviewed 89 senior female engineering students who graduated in 2005 from the

University of Illinois to discover the factors that influenced their decision to pursue an engineering degree. Two of the five most frequently cited factors pertained to teachers, with 73 percent of interviewees mentioning "Excellent math/science/technology teachers" and 55 percent crediting "Teachers who encouraged me to pursue my interest in math/science/technology." Based on their comprehensive review of this literature in 2003, Osborne et al. concluded that "the single most important change that could be made to improve the quality of science education would be the recruitment and retention of able, bright, enthusiastic teachers of science" (p. 1069). More than a decade after this observation, many schools are still inadequately staffed by high-quality math and science teachers, a problem that is even more pronounced at high-poverty and high-minority schools (NSB, 2016).

Race, ethnicity, and socioeconomic status. As mentioned in the introduction to this study, a key problem in the STEM pipeline relates to the persistent underrepresentation in STEM fields of non-Asian minorities, particularly African Americans and Hispanics, as well as those from families of lower socioeconomic means (Navarro et al., 2007).[2] Evidence from existing research suggests this problem likely has its roots in students' K-12 educational experiences (Tyson et al., 2007). For example, as Adelman (2006) pointed out, Latino students tend to have less access to high schools that offer high level math courses like trigonometry and calculus, and the poorest students in the nation are more likely to attend high schools that do not offer math above Algebra 2. Using data from the Education Longitudinal Study of 2002 (ELS:2002), Bozick and Ingles (2008) similarly showed that Asian and White students, as well as high SES

[2] Although the overwhelming homogeneity of the sample used in the current study limits the ability to engage in a discussion about race and ethnicity, its prominent role in the literature merits at least a brief overview here.

students, were more likely to take advanced placement classes that included precalculus and calculus. What is more, the researchers also found that, on average, students in the highest SES quartile outgained those students in the lowest SES quartile and those gains came in more advanced subjects.

Some scholars argue that these differences in STEM outcomes can be attributed to more than simple access to better schools and more advanced coursework. Osborne et al. (2003) point to a particularly interesting argument along these lines as it relates to students' attitudes toward science:

> Moreover, as Lemke (2001) cogently argues from a socio-cultural perspective, contemporary science is a product of European culture, and a middle-class subculture at that. For those who lie outside the orbit of such cultures by virtue of their ethnic origin or social status, the nature of what counts as explanation may be startlingly different. Changing students' minds, therefore, requires more than their assent to the bare facts, logical structure and epistemology of Western science. (p. 1073).

The authors go on to suggest that the struggle to engage underrepresented students with science cannot be construed as "an equivalent process for all demanding only logical thought and application […] rather, cultural and class difference may be a significant aspect of many pupils' attitudes toward science" (1073). These arguments lie outside the scope of the current study, but they remain important to consider in light of persisting disparities in STEM pipeline outcomes for underrepresented minority and ethnic groups.

Of course, the literature does contain some reason for hope in this area. In one of the earliest studies to use quasi-experimental techniques aimed at uncovering causality, Federman (2007) found that, all else equal, Asians and blacks in the NELS dataset had a greater likelihood of taking more math and science courses in high school. She also found that Asian males and Hispanic and black females were more likely to major in a technical field. Additionally, based on data from 4-year universities in Florida, results from work by Tyson et al. (2007) suggested that while Black and Hispanic students did, on average, complete lower-level high school courses, Black students who did take high-level courses were as likely to obtain a STEM degree as White peers who also obtained a bachelor's degree. Hispanics in the study had even greater probabilities of obtaining a STEM degree when compared to Whites.

Timing of information and exposure. A main focus of this study concerns whether the timing of college and career related information are related to student's mathematics course taking in high school and/or to their plans to major in a STEM field. Conceptually, this question flows from the idea that the number and intensity (level of difficulty) of science and math courses in high school have been positively associated with postsecondary outcomes ranging from attendance and persistence (Atanda, 1999; Byun et al., 2015; Schneider, Kirst & Hess, 2003; Schneider, Swanson, & Riegle-Crumb, 1998) to the likelihood of majoring in a STEM field (Trusty, 2007). Accruing a large number of math and science courses and following a succession of coursework leading to subjects such as calculus and physics likely requires a fair amount of planning on behalf of a student (Adelman, 2006). And since the traditional high school student only has four years to earn credits in these courses, he or she will likely need to begin this process as soon as possible. The sequential nature of mathematics courses heightens this need as one cannot typically take trigonometry before building a foundation in basic linear algebra.

The timing of this process is so important that students have been shown to benefit from starting their high school coursework trajectory as early as middle school algebra (Adelman, 2006). Of course, it is perhaps more likely that a student will succeed in this pursuit if he or she has at least considered attending college at all from a very early age. Otherwise, the student might not find the accumulation of numerous and advanced math and science credits worth the extra effort.

Given the links between advanced coursework and postsecondary STEM outcomes, a brief overview on the role of timing in the overall college choice process is merited before exploring the links between timing of information and the STEM pipeline outcomes specifically. Traditionally, the more general college choice process has been said to begin around the seventh grade and is referred to as the disposition stage discussed previously (Hossler & Gallager, 1987). Some researchers have argued, however, that predisposition likely begins before that, even as early as elementary school for some children (Eccles et al., 2004, Harding et al., 2017). Using data from the early 1980s, Eccles found that students who in the sixth-grade expressed plans to enroll in college were indeed significantly more likely to have been enrolled in college full-time when surveyed two years after high school graduation. This relationship held after accounting for important predictors of college enrollment such as parental education and family socioeconomic status. Though it relied on a small sample size, the longitudinal nature of the data lends added support to a logical conclusion that plans made early in students' education can lead to important postsecondary outcomes. Similarly, using a substantially larger sample size of students from New Hampshire, Harding et al. (2017) found that students who received college-related information before the seventh grade were significantly more likely to decide before middle school whether they would attend college. Those who decided this early were also significantly more likely to follow a college prep course of study in high school and to aspire to earn graduate degrees at some point. Neither of these studies, however, considered whether these early decision and information variables were related to plans to major in a particular field or to math and science high school course taking.

A number of researchers and scholars have discussed this notion of the importance of timely information as it relates to choosing a major (Beggs et al., 2008, Bonous-Hammarth, 2000) and to STEM majors specifically (Baker & Leary, 1995; Blustein et al., 2013; Cleaves, 2005; Maple & Stage, 1991; Maltese & Tai, 2011; Tai et al., 2006). Most of these discussions conclude that students simply do not receive enough, if any, information about pursuing STEM-related degrees or the preparation necessary for doing so. Whereas some authors have suggested a need for improved informational resources in high school (Cordova-Wentling & Camacho; Schneider et al., 2003; Zhang & Barnett, 2015), others have argued that intervention should begin in the middle grades and earlier (Baker & Leary, 1995; Barton et al., 2008; Dozier et al., 1997; Dell et al., 2011). Maltese and Tai (2010) support this claim based on their qualitative research involving interviews of 116 participants that were mostly post-/graduate students studying the sciences or individuals who were at the time employed in the scientific fields. During interviews, 65 percent of participants indicated that their interests in science began before the middle school years. The authors bolstered this notion with a subsequent analysis of NELS data that considered the role of various factors that influence students' persistence in eventually earning a STEM degree (Maltese & Tai, 2011). Results suggested that enrollment in science courses in high school and students' stated interest in math and science and beliefs in their ability at the time were significant predictors of eventual STEM degree completion. The authors conclude that these behaviors and attitudes were likely influenced by factors that precede the eighth grade.

Related work using these datasets has provided evidence that student factors in the middle school years exert an influence on students' choices to pursue STEM degrees and careers. Using NELS data to investigate the relationship between students' early (eighth grade) career expectations and postsecondary outcomes, Tai et al. (2006) found that among NELS participants earning baccalaureate degrees, those students who in the eighth grade expressed plans to be working in a science field at age 30 were significantly more likely to have earned a degree in a science field by the end of the survey. Specifically, they were almost twice as likely to have earned a life sciences degree and 3.4 times more likely to earn a degree in engineering or the physical sciences. However, as Tai et al. concluded,

> […] we should not overlook the likelihood that life experiences before eighth grade and in elementary school may have an important impact on future career plans [… our study suggests] that to attract students into the science and engineering, we should pay close attention to children's early exposure to science at the middle and even younger grades (p. 1144).

Few studies, however, have considered the influence of pre-eighth-grade factors (aside from background demographic variables) on these STEM pipeline outcomes from an empirical and quantitative perspective. This is, in large part, due to the limitations of education datasets. Those built from local or state-level participants often suffer from challenges related to small sample sizes or findings that are contested as not being generalizable. Nevertheless, in many cases, a study of this type can provide the only limited information currently available. In fact, a review of the literature uncovered only one such article. In this publication, Simpkins et al. (2006) tested a structural equation model that considered whether fifth-grade students' involvement in after-school math and science activities led to later enrollment in a higher number of math and science courses when those students were in high school. The model hypothesized that an increase would be seen through the after-school activities' effect on students' self-concept, interests, and importance placed on math and science. The authors concluded their models showed statistically significant support for this idea, suggesting that exposure as early as the fifth grade led to student choices to take more math and science classes. The data for this study, however, represent a very small sample size of only 227 students from the Michigan Childhood and Beyond Study and only pertain to those students that were in the third grade in 1987. Additionally, the models contained only limited controls for other factors such as student gender, grades, and socioeconomic status.

This need to consider students' experiences before the eighth great is echoed throughout the literature on STEM education and careers (Baker & Leary, 1995; Barton et al., 2008; Dozier et al., 1997; Dell et al., 2011; Maltese & Tai, 2010), and it is this idea that drives the empirical work of this study.

CHAPTER 3

DATA AND METHODS

The conceptual framework of this study suggests that students' very early (before eighth grade) exposure to information about college is associated with their likelihood of having taken advanced mathematics coursework in high school. These course taking patterns, in turn, should be associated with an increased likelihood of planning to major in a STEM or STEM related field. As discussed in the prior chapter, however, this process occurs under the influence of myriad factors. Any statistical models aimed at estimating the relationships between student's early exposure to information about college and the STEM pipeline outcomes of course taking, deciding to go to college, and choosing a major would need to account for the effects of the many other theoretically and conceptually driven controls.

The following sections of this chapter outline the general approach taken in this study to investigate the relationships between early exposure to information about college and advanced math taking in high school and/or planning to major in a STEM field in college. I begin with an overview of the data, followed by explanations regarding construction of the dependent and independent variables for each of the equations. I follow this by describing the estimation of the analytic models deployed in the study, including explanations for the selection of appropriate standard errors. The chapter concludes with a brief discussion of limitations.

Data Sources and Variable Construction

Data for this study come from the 2007 *Measuring Aspirations and Participation: New Hampshire High School Senior Survey (NHHSSS)* conducted by the New Hampshire Partnership for the Advancement of Postsecondary Education Research (NHPAPER). NHPAPER conducted the NHHSSS a total of six times, beginning with a 2002 pilot study involving 2,408 graduating seniors that attended 21 of the state's public high schools at the time. The number of students responding to the survey increased until the 2005 survey, which considered survey results from some 8,500 seniors representing 63 public and 8 private schools in New Hampshire. The final iteration of NHHSSS occurred in 2007 and garnered responses from nearly 7,500 seniors from 51 public and 3 private schools in the state.

Related to a similar annual survey in Vermont, the NHHSSS asked seniors a range of questions related to their personal and family backgrounds, high school experiences, and plans regarding their lives after high school (NHPAPER. 2002). Background information was obtained through official records as well as responses based on students' gender, race/ethnicity, family income and living situations. Other information collected by the survey measured students' course-taking behaviors and extra-curricular involvement. Participants responded, for example, to questions related to their satisfaction with their high school classes and whether they pursued a college preparatory path. Perhaps most germane to the purpose of the survey were questions related to students' plans regarding postsecondary education. Respondents provided information related to topics such as the timing and sources of their information about college, whether they planned to attend postsecondary education, and the highest degree to which they aspired.

Participants in some cases were asked to address different questions depending on whether they planned to attend college immediately after finishing high school. Those choosing to enroll in the following spring answered questions more specific to which NH institutions they were considering, their anticipated major field of study, and whether they planned to enroll out-of-state. Those not planning to immediately enroll in a postsecondary institution were asked to respond to questions about their future career plans (*e.g.*, which industries they were considering) and whether they planned to pursue more education at a later date. A final section of the NHHSSS targeted only those students that had participated in the state's career and technical education (CTE) or vocation education offerings.

In this study I focus on responses from public school students that were high school seniors in New Hampshire in the final year of the NHHSSS (the 2006-2007 schoolyear). Particularly relevant to the current study are these students' responses to questions related to the timing of conversations with their parents regarding what to do after high school. These items consider students' experiences as far back as elementary school. Additionally, the survey data contains other relevant demographic information, including variables related to social, cultural, and human capital, as well as responses regarding students' postsecondary aspirations.

Seniors responding to the survey used for this study represented fifty-one public high schools (63% of all public NH high schools in 2007) and three private high schools. Each institution chose a time between April and June of 2007 to administer the survey.

Seniors were encouraged–but not required–to participate. Of the 10,743 eligible seniors at participating high schools, 7,472 completed and returned the surveys, yielding a response rate of 64%. This does not include the remaining NH high school seniors at non-participating schools. The final analytic sample in the full model contained 6,101 students.

The sampling design of the NHHSSS did not ensure that the participant makeup was representative of the state of New Hampshire, nor can the sample be construed as nationally representative. However, Table 1 places this study's sample in the context of the entire state of New Hampshire as well as other states in the New England area: Vermont, Maine, Rhode Island, and Connecticut.[3] Based on data drawn from the 2007 NHHSSS and the 2007 American Community Survey (ACS) from the United States Census Bureau, this table compares values for a number of similar factors observed in each dataset. In terms of racial and ethnic composition, the data for this study reflect a rather homogenous group of individuals, with around 94 percent of students reporting being white only and non-Hispanic. According to ACS (2007) data, this is in keeping with the state of New Hampshire as a whole, as well as Vermont and Maine. Rhode Island and Connecticut are noticeably more diverse by comparison.

In terms of educational attainment, Table 1 shows students' responses reflect a degree of similarity with the ACS (2007) data for the area. One of the larger discrepancies relates to Rhode Island's 17 percent of the state population with less than a high school degree as compared to students' reports of only six percent for that same category. Both the study sample and the NH state population also have modestly higher

[3] New York and Massachusetts are excluded based on the influence of the demographic makeup from the states' large metropolitan areas.

percentages of those with “Some college or Associate’s” degrees. Overall, however, the reported educational attainment of parents in the sample appear to align with what the ACS reports for the area.

These comparisons should be interpreted with caution, however. Though the NHHSSS survey asked students to report education levels for both parents, a number of students had missing or incomplete data for one or both parents. To simplify comparisons for Table 1, I chose to report only on mother’s education. In the analytic models, however, I attempt to account for both parents’ education when possible. Thus, similarities and differences in educational attainment shown in Table 1 are not based on perfectly comparable measures and could be a reflection of differences in attainment by gender in each area.

The ACS collects a number of data points regarding income and earnings. None of these matches perfectly with the data collected in the NHHSSS. Nevertheless, to provide some context I supplied the ACS numbers for average 12-month earnings for full-time employees (Table 1). In this regard, New Hampshire looks more like Rhode Island and Connecticut as opposed to Vermont and Maine, which more closely align with New Hampshire in terms of racial and ethnic makeup. In fact, the near 21 percent of New Hampshire full-time earners in the “75,000 or more” exceeds that of Vermont (12.6 percent) by more than eight percent and doubles the percentage seen in Maine (10.9 percent). Students in the NHHSSS did not report their parents’ earnings individually, however. Rather, they provided their family household income. Though a large portion of students responded that they “Don’t Know” this information, the distribution of those reporting is weighted toward the higher end of the options. That is, nearly thirty percent

Table 1: Comparison of Dataset Demographics to all of NH and Surrounding States

	Dataset	New Hampshire	Vermont	Maine	Rhode Island	Connecticut
Population (estimates)	n=6,101	1,315,828	621,254	1,317,743	1,057,832	3,502,309
Female	53.2%	50.8%	50.9%	51.3%	51.7%	51.3%
Race & Hispanic/ Latino Origin						
Missing	1.3%	N/A	N/A	N/A	N/A	N/A
One Race	95.9%	98.8%	98.4%	98.2%	97.9%	98.0%
White	92.3%	94.8%	96.1%	95.2%	82.8%	79.6%
Black/African American	1.1%	1.0%	0.6%	1.1%	5.6%	9.4%
American Indian	0.5%	0.2%	0.3%	0.6%	0.3%	0.2%
Asian	1.7%	2.0%	1.1%	1.0%	2.8%	3.4%
Native Hawaiian/Pacific Islander	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%
Other	N/A	0.8%	0.2%	0.3%	6.4%	5.4%
Two or More Races	2.8%	1.2%	1.6%	1.8%	2.1%	2.0%
Hispanic or Latino (any race)	2.7%	2.5%	1.3%	1.1%	11.2%	11.5%
Hispanic/Latino Missing	1.3%	N/A	N/A	N/A	N/A	N/A
White alone, non-Hispanic/Latino	93.7%	93.2%	95.2%	94.5%	78.8%	74.0%
Educational Attainment[ab]						
Less than HS Graduate	6.1%	9.5%	9.7%	10.6%	17.0%	12.0%
HS Graduate[c]	28.2%	31.0%	32.6%	36.3%	29.0%	29.5%
Some College or Associate's	30.6%	27.0%	24.1%	26.4%	24.2%	23.9%
Bachelor's	20.9%	21.0%	20.7%	17.5%	18.0%	19.3%
Graduate/Professional	11.8% [d]	11.5%	12.9%	9.2%	11.8%	15.4%
Missing	2.5%	N/A	N/A	N/A	N/A	N/A
12 Month Earnings for full-time workers						
Less than $25,000	N/A	15.6%	20.1%	22.8%	16.5%	13.8%
$25,000 to $49,999	N/A	41.4%	49.1%	47.1%	30.7%	35.8%
$50,000 to $74,999	N/A	22.2%	18.3%	19.2%	23.4%	24.6%
$75,000 or more	N/A	20.9%	12.6%	10.9%	18.3%	25.9%
Family Income [d]						
Less than $25,000	6.0%	N/A	N/A	N/A	N/A	N/A
$25,000 to $49,999	13.2%	N/A	N/A	N/A	N/A	N/A
$50,000 to $74,999	15.2%	N/A	N/A	N/A	N/A	N/A

Table 1 continued

	Dataset	New Hampshire	Vermont	Maine	Rhode Island	Connecticut
Family Income [d]						
$75,000 or more	29.5%	N/A	N/A	N/A	N/A	N/A
Don't Know	34.3%	N/A	N/A	N/A	N/A	N/A
Missing	1.6%	N/A	N/A	N/A	N/A	N/A
Household Type						
In married-couple family	78.3%	65.1%	59.6%	62.5%	58.1%	62.1%
In other households[e]	21.7%[f]	31.9%	37%	34.6%	38.2%	34.6%

Notes: State-level data taken from 2007 American Community Survey (ACS) Table S0501 "Selected Characteristics of the Native and Foreign-Born Populations: 2007 American Community Survey 1-Year Estimates." [a] For ease of comparison, statistics from sample are relative to mother only. [b] Includes equivalency in ACS data. [c] The 11.8% figure from the dataset includes 235 students whose mother they reported as having "Some graduate or professional school." [d] ACS category is "Earnings in the past 12 months (in 2007 inflation-adjusted dollars) for full-time, year-round workers; Population 16 years and over with earnings," whereas in the sample, students reported total family income. [e] Includes 29 students with a missing value for living situation.

of students in the responded with $75,000 or more for their family's household earnings.

Finally, each data source contained information related to household type. Whereas the overwhelming majority of students in the NHHSSS (78.4 percent) lived in a married couple family, these percentages were much smaller at the various state levels. This likely stems from the fact that the NHHSSS sample only collects living situation information from young people, who are more likely to still live with their parents than the average ACS respondent, who could come from a much larger age group.

Though not representative of the larger national student population or possibly even the state of New Hampshire, the NHHSSS data contain responses to questions related to timing and information that are not available in larger nationally representative datasets. Access to these responses allows for an investigation into associations that are presently assumed to be true based only logic and theory. The methods employed in this study–and detailed in subsequent sections–do not allow for causal modeling or true testing of theories or conceptual frameworks; however, these data do allow me to establish an important first step in that direction.

Dependent variables. In this study, I am interested in three outcomes. The first, *AdvancedMath,* is a binary variable representing whether a student reported having studied at least two years in the subject area of "Algebra II/Trigonometry/Pre-Calculus/Calculus/Statistics" and is categorized as either "Yes" or "No." The requirement for two years rather than one accounts for Burkam and Lee's (2003) characterization of Algebra II as a mid-level rather than advanced math course. In the 2006-2007 school year, graduation requirements in the state of NH only called for three mathematics courses, including an algebra credit that must be earned in a course that extends beyond pre-algebra principles (Tracy, 2006). Thus, advanced math course taking is likely the result of student choice rather than forced requirements. As shown in Table 2, approximately half of the students included in this study meet the criteria I established as having taken advanced math courses. This does not change when considering differences by male and female status.

Table 2: Summary Statistics of Dependent Variables in Aggregate and by Gender

	Aggregate (n=6101)				Male (n=2853)		Female (n=3248)	
	Mean	St. Dev	Min	Max	Mean	St. Dev	Mean	St. Dev
Advanced Math	0.49	0.50	0	1	0.50	0.50	0.49	0.50
Extra Science	0.55	0.50	0	1	0.53^	0.50	0.57^	0.49
STEM Major	.20	.40	0	1	0.23^	.42	0.16^	0.37

Notes: ^ Denotes significant differences between disaggregated coefficients at a minimum of p<.05.

Although a determination of whether students took "advanced science classes" in high school is not easily made based on the NHHSSS, I was able to create a second dependent variable in this study, *Extra Science*, as a binary measure that designates whether a student reported taking either four or five years of science in high school, which exceeds the three years typically required by states or local education agencies. Around 55 percent of students in the study fit this description. Females were significantly more likely to belong to this category with 57 percent taking more than three years compared to the 54 percent of males. The difference was significant at the $p<.01$ level.

The third dependent variable in this study, *STEM*, represents whether students expressed plans to major in a field of study that has connections to STEM. This is also a binary variable and defined as either "Yes" or "No." Since the NHHSSS was not designed to focus on STEM explicitly, categories students were allowed to choose from do not align perfectly with STEM majors. As such, I base inclusion criteria for STEM on the 2016 revised list of STEM-designated degree programs identified by U.S. Immigration and Customs Enforcement (ICE) as suggested by the U.S. Department of Education. As the document states:

> The STEM Designated Degree Program list is a complete list of fields of study that DHS considers to be science, technology, engineering, or mathematics (STEM) fields of study for purposes of the 24-month STEM optional practical training extension described at 8 CFR 214.2(f). Under 8 CFR 214.2(f)(10)(ii)(C)(2), a STEM field of study is a field of study "included in the Department of Education's Classification of Instructional Programs taxonomy within the two-digit series containing engineering, biological sciences,

mathematics, and physical sciences, or a related field. In general, related fields will include fields involving research, innovation, or development of new technologies using engineering, mathematics, computer science or natural sciences (including physical, biological, and agricultural sciences)."

Based on this explanation from federal guidelines and its accompanying list,[4] I include the following responses from the NHHSSS in the categorization of STEM: agricultural and natural resources, architecture and related programs, aviation, biological and life studies, computer and information technologies, engineering, mathematics, physical sciences, and psychology. Including a number of these fields (e.g., health professions) may mean that students are considered as expressing plans to pursue postsecondary study in a STEM field when their intended major does not appear on the ICE list. However, excluding these fields could also have the opposite effect. There is also some debate among policy makers and researchers whether "health professions" should be classified as STEM. I chose the more conservative route of excluding this option in the construction of the dependent variable. Regrettably, there is no perfect solution, and this must be considered a limitation of the study. It should be mentioned as a final note regarding the construction of this variable that I included students who indicated they do not plan to enroll in postsecondary education immediately after high school by assigning them to the "no" category, given they are not planning to pursue a STEM field of study (or any for that matter)[5].

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[4] Both the ICE STEM Designated Degree Program List and the 2007 NHHSSS survey are included as appendices to this study.

[5] Models were also estimated with a smaller sample that excluded students not planning to attend college. Results were substantively similar. As such, I include those not planning to attend college for purposes of comparing the same samples across outcomes.

A return to Table 2 shows that 20 percent of students in the survey expressed plans to pursue a major in a STEM field as defined in this study. This number fits at the lower end of findings based on work using the nationally-representative Beginning Postsecondary Study dataset (Chen, 2013), wherein the author reported that "about 28 percent of bachelor's degree students and 20 percent of associate's degree students entered a STEM field (i.e., chose a STEM major) at some point within 6 years of entering postsecondary education in 2003-2004" (p. iv). However, given the mixture of students anticipating both two- and four-year degrees, the twenty percent figure from the NHHSSS is perhaps not surprising. Table 2 also presents differences between males and females for this variable. As might be predicted by the literature 16 percent of females planned to major in a STEM field compared to 23 percent of males in the sample. This difference is statistically significant; however, it does not account for any other of the factors that are described below.

Explanatory variables. The primary predictor variable of interest in this study, *Parent Conversations,* is drawn from students' response to the question "when did you begin to talk with your parent(s) about what to do after high school?"[6] Students were given options beginning with "sixth grade or earlier" and increasing by one grade level at a time until "twelfth grade." A final option allowed students to answer "I haven't talked with my parent(s) about my plans." In constructing a variable to represent these I

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[6] The NHHSSS also includes a question that asks "When did you first receive information about postsecondary education" and includes similar response choices. Although this question more specifically addresses postsecondary education and appeals to more generic sources of information, 989 students (16.0 percent) in the sample have a missing value for this question. Given such a large portion of the sample did not select a response for this variable that is associated with clear implications, I opted to focus on the timing of parental conversations, which has far fewer instances of missing values (174; 2.8 percent).

Table 3: Descriptive Statistics for Independent Variables

	Aggregate (n=6101)				Males (n=2853)		Females (n=3248)	
	Mean	**St. Dev.**	**Min**	**Max**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**
Parent Conversations								
Seventh Grade or Before	0.20	0.40	0	1	.16	.37	.23	.42
Eighth or Ninth Grade	0.27	0.45	0	1	0.25	0.44	0.29	0.45
After Ninth Grade or Never[a]	0.50	0.50	0	1	0.55	0.50	0.46	0.50
Missing Value	0.03	0.17	0	1	0.03	0.18	0.02	0.15
Female	0.53	0.50	0	1				
Underrepresented Minority	0.07	0.25	0	1	0.07	0.25	0.06	0.24
GPA	3.21	0.54	0.14	4	3.11	0.57	3.30	0.51
Aspirations								
Less than 4 year degree[a]	0.18	0.38	0	1	0.23	0.42	0.14	0.34
Bachelor's Degree	0.31	0.46	0	1	0.30	0.46	0.31	0.46
Graduate Degree	0.37	0.48	0	1	0.32	0.47	0.41	0.49
Undecided	0.09	0.29	0	1	0.09	0.29	0.09	0.29
Missing Value	0.06	0.23	0	1	0.06	0.25	0.05	0.22
Living Situation								
Two Parents	0.78	0.41	0	1	0.80	0.40	0.76	0.42
One Parent[a]	0.17	0.37	0	1	0.15	0.36	0.18	0.38
Other	0.05	0.21	0	1	0.04	0.19	0.06	0.23
Missing Value	0.00	0.06	0	1	0.00	0.07	0.00	0.06
Family Income								
Less than $25,000	0.06	0.24	0	1	0.05	0.22	0.07	0.25
$25,000 - $49,999	0.13	0.34	0	1	0.13	0.34	0.13	0.34
$50,000 - $74,999[a]	0.15	0.36	0	1	0.17	0.37	0.14	0.35
$75,000 - $99,999	0.13	0.34	0	1	0.16	0.36	0.12	0.32
$100,000 or more	0.16	0.37	0	1	0.19	0.39	0.14	0.34
"Don't Know"	0.34	0.47	0	1	0.29	0.45	0.39	0.49
Missing Value	0.02	0.13	0	1	0.01	0.13	0.02	0.13
Parent Education								
None w/4yr degree[a]	0.50	0.50	0	1	0.49	0.50	0.52	0.50
One w/4 yr degree	0.23	0.42	0	1	0.24	0.42	0.23	0.42

Table 3 continued								
	Aggregate (n=6101)				**Males (n=2853)**		**Females (n=3248)**	
	Mean	**Standard Deviation**	**Min**	**Max**	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**
Parent Education								
Both w/4 yr degree	0.25	0.43	0	1	0.26	0.44	0.23	0.42
Missing values	0.02	0.13	0	1	0.02	0.14	0.01	0.12
Math Instruction								
Excellent	0.26	0.44	0	1	0.30	0.46	0.22	0.42
Satisfactory[a]	0.51	0.50	0	1	0.49	0.50	0.52	0.50
Unsatisfactory	0.17	0.38	0	1	0.14	0.35	0.20	0.40
Was not taught	0.04	0.20	0	1	0.04	0.20	0.04	0.20
Missing value	0.02	0.14	0	1	0.02	0.15	0.02	0.12
Science Instruction								
Excellent	0.25	0.43	0	1	0.28	0.45	0.22	0.41
Satisfactory[a]	0.52	0.50	0	1	0.51	0.50	0.53	0.50
Unsatisfactory	0.18	0.38	0	1	0.15	0.36	0.20	0.40
Was not taught	0.04	0.19	0	1	0.04	0.19	0.04	0.19
Missing value	0.02	0.14	0	1	0.02	0.15	0.02	0.12
Tech Instruction								
Excellent	0.35	0.48	0	1	0.40	0.49	0.31	0.46
Satisfactory[a]	0.50	0.50	0	1	0.47	0.50	0.53	0.50
Unsatisfactory	0.09	0.29	0	1	0.08	0.27	0.10	0.30
Was not taught	0.04	0.19	0	1	0.04	0.19	0.04	0.20
Missing value	0.02	0.15	0	1	0.03	0.16	0.02	0.14

Notes: [a] Denotes reference category

arranged them by groups[7] in hopes of alleviating concerns that students may have trouble remembering exactly when these conversations first happened. As seen in Table 3, the first category includes students responding with either "sixth grade or earlier" or "seventh grade" and accounts for 20 percent of the sample. For ease of discussion, these students are subsequently referred to as *early conversers.* A second category, *mid-level*

[7] Though I construct nearly all variables in the study to be categorical, in the analytic models they are entered as factor variables using STATA 13's *i.var* function, which treats the categorical variable as a set of dummy variables for each value, excluding a default or defined reference category. Descriptive statistics reflect this binary categorization. Further rationale for this decision is supplied in the *Analytic Models* section of Chapter 3.

conversers, combines 27 percent of the sample and includes those who responded either "eighth grade" or "ninth grade." Fifty percent of students chose responses after the ninth grade, including the option stating they did not speak with their parents about what to do after high school. I included those who never spoke to parents in this grouping as they only comprised 3.7 percent of the final sample and thus not quite large enough to serve as their own group for the purposes of analysis. These students are referred to as *late conversers.* A final category, *missing value*, includes individuals with missing responses for the variable (3 percent of the sample).

It bears mentioning that this variable is subject to the possibility of self-selection bias. That is, although it can be used to account for the timing of students' earliest conversations with parents, it cannot account for whether the student or the parent initiated. This may be a key difference if a student's intrinsic motivation or some other factor drove him or her engage in these discussions. In such cases, it might be that these internal factors explain the relationship of the conversations and the outcomes rather than the timing. Unfortunately, discerning such a link is not possible given the other limitations of this study.

The theoretical frameworks guiding this study point to several other important factors that might help to better explain students' course taking behaviors and plans. Chief among these other factors is the student's gender. This is included in aggregated models as a binary variable to denote whether a student is *Female*. As suggested by prior research on the STEM pipeline, analytic models are also estimated separately based on this variable.

The dichotomous variable *URM* denotes whether a student belongs to racial and ethnic groups that are underrepresented in STEM education and careers. Students in the sample satisfy the criteria for this category if they are nonwhite, non-Asian, or Hispanic. Though Asians are often included in minority classifications, for the purposes of this study, it is important to recognize that Asian students tend to be *over-represented* in STEM fields. Additionally, the survey considered “Asian” as a separate response from “Native Hawaiian or other Pacific Islander.” The latter are classified in this study as underrepresented. Such decisions are defensible in the literature; however, these definitions may not matter as the sample used in this study is overwhelmingly white and the percentage of students classified as URM is extremely small.

Students’ academic ability level is measured by *GPA*. Although the survey instrument only includes a space for self-reported GPA category, the final dataset includes an official continuous measure for each student that was collected from each school by the NHPAPER group. In this study I opt for using the official continuous version. In keeping with the literature on the topic, I include a control for students’ postsecondary aspirations. This construct groups students’ responses into those with reported aspirations of an earning less than a bachelor’s degree, a bachelor’s (reference group), or any type of graduate degree. Other categories of the aspirations variable denote whether a student was undecided or had a missing value for the response.

Given that the primary predictor variable in the study considers students’ conversations with their parents, I also include as a control a categorical variable based on the student’s living situation. Responses were grouped into those for those living in homes with “two parents”, “one parent” and those in “other” living situations. Those with missing values are included in a final category. Students' family income was measured in self-reported categories of $25,000 bands. These groupings represent family incomes of "Less than $25,000"; "25,000 to $49,999"; "$50,000 to $74,999"; "$75,000 to $99,999" (reference group); and "$100,000 or more." Categories were also created for those who responded "Don't know" and for those with missing values. Additional family controls include a parental education variable that measures whether students had one parent, both parents, or no parents with at least a four-year degree, as well as a variable that measures what students reported their parents expected them to do after graduating high school. Non-postsecondary education related responses for the latter variable are grouped together in an "Other" category. Both variables include an added category for "Missing Value."

A final group of variables contains academic and classroom experience factors. Students were asked in the survey to rate the quality of their instruction in math, science, and technology. Specifically, they were to respond with "Excellent," "Satisfactory," "Unsatisfactory," and "Wasn't taught" and were asked to apply this scale to the following areas: "Understand and apply [mathematics/science/technology] in everyday life." From the three separate questions I created the variables *Apply Math, Apply Science, and Apply Tech.* As with other variables in the study, a "Missing Value" category was added to each.

Table 3 provides descriptive statistics for each of the independent variables detailed above. Overall, only about one in five students in the sample were early conversers, while more than a quarter qualified as mid-level, leaving about half the sample that were late conversers. The sample was divided almost evenly between males and females, with the average student in the sample having a GPA of around 3.2. As mentioned above, less than 10 percent of the sample were those belonging to a group that is typically underrepresented in STEM education and careers. Around two-thirds of the sample aspired to either a bachelor's or a graduate degree in college.

Regarding family characteristics, almost three-quarters of the sample lived with both parents. Around 30 percent of students reported that they "Do not know" their family income. Six percent reported coming from families that earned less than $25,000 per year. The remainder of the students were split fairly evenly among the four categories ranging from "25,000 to $49,999" to "More than $100,000" ($50,000 increments). Whereas half the sample reported that neither parent had a four-year degree, the other half reported having at least one parent with at least a bachelor's degree. Sixty-five percent of students reported that their parents expected them to pursue at least some college education after high school, with the majority expectation being "attending a four-year institution."

In terms of academic variables, on average, students in the sample reported nearly identical ratings for classroom instruction in terms of applying math and science to real life. In both cases, more than a quarter of students reported that their experiences were "Excellent" and slightly around half responded that instruction was "Satisfactory." While this percentage was the same for students reporting "Satisfactory" experiences in terms of technology instruction, students were more likely to rate their experiences in these areas as "excellent."

Table 3 also includes a breakdown of the independent variables by sex. Considering the sample's characteristics along these lines, males were less likely than females to be early conversers (16 percent and 23 percent, respectively) and more likely to be categorized as late conversers (55 percent vs. 46 percent, respectively). Females' GPAs were on average nearly two-tenths of a point higher than that of the average male in the sample. Females were also more less likely to aspire to earn less than a four-year degree and more likely to aspire to earn a graduate degree.

Overall, males and females tended to come from the same family backgrounds; however, there were a few differences. Males were somewhat more likely to live with both parents and were similarly more likely to come from the highest earning families. Females, however, were much more likely than males to report they did not know their family's income (39 percent vs. 29 percent, respectively). Additionally, 58 percent of females reported that their parents expected them to attend a four-year college after high school while just under half of males in the sample said the same.

Finally, Table 3 shows that the academic experiences of males and females appear to have differed to at least a modest degree. Females were much less likely than males to report that their instruction in math and science was "Excellent" and much more likely to report that it was "Unsatisfactory." The largest of these discrepancies, however, relates to instruction in applying technology in students' daily lives. Females were nine percentage points less likely than males to rate this area of instruction as "Excellent." However, whereas with math and science instruction, the differences were made up in terms of more females rating instruction as "Unsatisfactory," with regards to technology, they seemed to be more willing to report that instruction was "Satisfactory" if not "Excellent.

Analytic Models

The binary nature of this study's three outcomes (advanced math course taking, taking four or more science courses, and planning to major in STEM) indicates the use of the probit regression as the most appropriate method of analysis. Though some important econometricians argue that a Linear Probability Model might suffice, the education literature tends to favor Probit models for a few reasons. The most important, however, is that a probit model fixes the latent outcomes of predicted probability of success between the values of zero and one. This prevents the maximum likelihood estimator from leading to a predicted probability of success that is either negative or exceeds 100 percent. Other researchers debate over the choice of probit over logistic regression. Long and Freese (2014), however, suggest that estimated coefficients have negligible differences between approaches. Furthermore, the results of probit regressions lend to more intuitive interpretations as coefficients of interest indicate changes to predicted probability of success rather than changes to logged odds. To further ease interpretation, I have reported the results of all statistical models in the study in terms of average marginal effects and first differences. I have also included in each model a vector of fixed effects for the students' school.

In models analyzing the full sample, I clustered standard errors at the school level, which attempts to account for possible correlations among students that attended the same school. Clustering also provided more conservative estimates of standard errors in hopes of reducing the likelihood of a Type 1 error. Due to complications that can arise when using very small clusters, two schools that had 25 or fewer students represented in the sample were combined into a new "Small Schools" category. For this same reason, I did not cluster standard errors when estimating models disaggregated by gender.

In order to establish whether a baseline connection exists between the timing of students' conversations with their parents and their advanced math course taking behaviors, I first fit a simple model following Equation 1, where $\boldsymbol{C}$ represents the year groupings for student/parent conversations and $\boldsymbol{S}$ denotes the school fixed effects.

(1) $Advanced\ Math = \alpha + \boldsymbol{C\delta} + \boldsymbol{S\theta} + \varepsilon$

I then estimated a subsequent series of equations, each time adding a new set of theoretically relevant variables commonly explored in the literature. These included a vector of personal characteristics $\boldsymbol{P}$; family factors, $\boldsymbol{F}$; and math instruction satisfaction controls, $\boldsymbol{M}$.

(2) $Advanced\ Math = \alpha + \boldsymbol{C\delta} + \boldsymbol{P\beta} + \boldsymbol{S\theta} + \varepsilon$

(3) $Advanced\ Math = \alpha + \boldsymbol{C\delta} + \boldsymbol{P\beta} + \boldsymbol{F\lambda} + \boldsymbol{S\theta} + \varepsilon$

(4) $Advanced\ Math = \alpha + \boldsymbol{C\delta} + \boldsymbol{P\beta} + \boldsymbol{F\lambda} + \boldsymbol{M\gamma} + \boldsymbol{S\theta} + \varepsilon$

By estimating multiple models in this fashion I was able to explore whether the conversation variables $\boldsymbol{C}$ would significantly predict the outcome net of the influence of the subsequent introduction other variables that do not represent new contributions to the literature.

In keeping with prior studies, Equations 1 through 4 are estimated based on the full analytic sample and then re-estimated for males and females separately for a few important reasons. The first is that existing literature has found that gender explains a substantial portion of the variance in models related to STEM outcomes, meaning that including this variable can easily mask the explanatory power of other important variables without improving our existing understanding of the issue. Second, as theorized by Eccles (1987), the experiences of males and females are so different they require separate analyses.

Following the estimation of models predicting students' advanced math course taking behaviors, I turned my attention to the second outcome variable, *Extra Science*. Equations 5 through 8 illustrate the approach I employed, which followed the same taken when predicting *Advanced Math*:

(5) $Extra\ Science = \alpha + \boldsymbol{C\delta} + \boldsymbol{S\theta} + \varepsilon$

(6) $Extra\ Science = \alpha + \boldsymbol{C\delta} + \boldsymbol{P\beta} + \boldsymbol{S\theta} + \varepsilon$

(7) $Extra\ Science = \alpha + \boldsymbol{C\delta} + \boldsymbol{P\beta} + \boldsymbol{F\lambda} + \boldsymbol{S\theta} + \varepsilon$

(8) $Extra\ Science = \alpha + \boldsymbol{C\delta} + \boldsymbol{P\beta} + \boldsymbol{F\lambda} + \boldsymbol{I\gamma} + \boldsymbol{S\theta} + \varepsilon$

An important change here is that the vector of $\boldsymbol{I}$ variables measures satisfaction with students' science instruction and replaces the corresponding math related variables from the prior set of models.

Models 9 through 12 express the process for estimating models based on the final dependent variable *STEM*:

(9) $STEM = \alpha + \boldsymbol{C\delta} + \boldsymbol{S\theta} + \varepsilon$

(10) $STEM = \alpha + \boldsymbol{C\delta} + Advanced\ Math\varphi + Extra\ Science\rho + \boldsymbol{K\zeta} + \boldsymbol{S\theta} + \varepsilon$

(11) $STEM = \alpha + \boldsymbol{C\delta} + Advanced\ Math\varphi + Extra\ Science\rho + \boldsymbol{K\zeta} + \boldsymbol{P\beta} + \boldsymbol{S\theta} + \varepsilon$

(12) $STEM = \alpha + \boldsymbol{C\delta} + Advanced\ Math\varphi + Extra\ Science\rho + \boldsymbol{K\zeta} + \boldsymbol{P\beta} + \boldsymbol{F\lambda} + \boldsymbol{S\theta} + \varepsilon$

As with *Advanced Math* and *Extra Science*, the first model (Equation 9) predicting the probability a student expressed plans to major in a STEM field included only the conversation variables, ***C***, and the school fixed effects variables ***S***. I then introduced the actual (not predicted) *Advanced Math* and *Extra Science* variables (Equation 10) to examine whether any relationships between STEM and parent conversations might be explained through the connection of the timing of conversations and course taking. I also added another vector of variables ***K*** that measures students' satisfaction with classroom instruction, adding technology instruction factors to the math instruction variables ***M*** and science instruction variables ***I*** from the prior models above. The vectors of personal variables, ***P***, and family variables, ***F***, are the same as used in Equations 1-8.

In keeping with the models predicting *Advanced Math* and *Extra Science*, I estimated models predicting *STEM* in the aggregate and then separated by male and female status. Throughout the estimation process, I relied in each case on the probit method described above, clustering standard errors at the school level in aggregate models.

Finally, when comparing marginal effects between models disaggregated by gender, I performed additional significance tests of those parameters based on Equation 14 (DeMarris, 2004)

(13) $$t = \frac{b_j - b_k}{\sqrt{(seb_j^2 + seb_k^2)}}$$

where b_j, seb_j, b_k, and seb_k are the parameter coefficients and standard errors for males and females, respectively. All tests are conducted at the 95 percent confidence level.

Missing data. There are a number of ways to handle cases of missing data. In instances of data that are missing completely at random (MCAR), list-wise deletion of all individuals with missing data is the simplest approach. Since I do not believe the data for this study meet the MCAR criteria, I reserved list-wise deletion for the fewest instances possible. These include students I removed from the original sample (n=7,472) that had missing values for the dependent variables (529 for *AdvMath,* 67 for *Extra Science*, and *474* additional for *STEM*). I further excluded 42 students with either missing values for *GPA* or those whose GPA was entered as 0 along with 17 students with missing values for female and 9 students that selected more than 3 of the choices for "race" prompted by the NHHSSS. While I considered imputing these values, I believed the small number of cases allowed for deletion to be the most parsimonious choice without comprising the approach of the study. In all other cases, I attempted to retain as many students as possible in the sample by creating a designation in each categorical variable to include those individuals that had a "Missing value" for that particular factor.

Following this approach carries at least one caveat, however. Including "Missing Value" as an option in categorical variables creates a situation in which variables can no-longer be classified as ordinal, interval or ratio, which makes the interpretation of regression coefficients much less intuitive. An appealing work-around to this would be to transform categorical variables into *c* dummy variables, where *c* represents the number of possibilities (including "Missing Value") in each category. When estimating models, one of these dummy variables would then be excluded as the reference group. This approach has limitations, though, as the variables are linked in such a way that complicates certain post-estimation approaches (Long & Freese, 2014). For example, if the dummy variable approach were applied to the variable *Living Situation*, with "One Parent" set as the reference group, the resulting coefficient from calculating average marginal effects from a Probit regression would reflect the change in the dependent variable when the value for One Parent is changed, all else constant. Of course, this has no practical application when considering an observation that reported a "Two Parent" living situation. If a "yes" response for "Two Parent" is held constant and then the "One Parent" response is changed to "yes," the observation would in effect be considered as belonging to two mutually exclusive categories at the same time.

To deal with this scenario, Long and Freese (2014) suggest entering all such categorical variables into analytic models as factor variables (e.g., *i.var* in Stata). The authors favor this approach as statistical software packages (such as Stata 13, which I used in this study) are programmed to take these special cases of variables into account when calculating quantities such as first differences and average marginal effects. This is the approach I have adopted in the current study.

Limitations

This study faces a few limitations that need to be addressed. The data considered herein represent a selection of students from a small and heterogeneous state. They are not representative of the state as a whole, nor are inferences drawn from these data to be considered nationally-representative. The data also reflect self-reported responses rather than official transcript data. The lone exception to this is the variable for *GPA*, which is an official measure supplied to the NHPAPER group by the schools involved in the study. Although many researchers have previously defended the use of student self-reported data,[8] not all equally agree on the reliability or validity of these responses. Additionally, variables related to students' very early conversations are based on their

[8] See, for example, Bahrick, Hall, and Berger (1996) and Kuncel, Credé, and Thomas (2005), for a deeper discussion and review of this area of the literature.

recollections from many years past. Work by Bahrick, Hall, and Berger (1996), however, has provided some support for students' ability to recall information from several years prior, with greater accuracy seen at higher levels of achievement. The primary predictor variables also refer only to the timing of conversations students had with parents about what to do after high school, and were not specifically about STEM-related topics. Finally, a lack of official transcripts forces models to rely on reported hours attempted in math course groupings rather than on the actual mathematics courses completed.

Finally, though the approach in this study is unable to account for potential self-selection bias for the dependent variables or account for unobservable factors beyond those controlled for using the school-level fixed effects, the independent variables of interest (time at which student first began speaking with their parents about college) capture a temporal element that can perhaps mitigate some of these challenges.

Despite these limitations, the distinct data used in this study allow me to begin to consider factors that existing research in the STEM pipeline has identified as crucial but has thus far been unable to explore. Specifically, the STEM pipeline literature has repeatedly stressed the importance of students' early life and school experiences as being critical to the development of affinity for math and the sciences and the formation of plans to pursue a STEM career. These early life experiences, however, have almost exclusively been researched using small sample, qualitative approaches. Given the lack of larger, nationally-representative datasets that include variables related to these early experiences, the NHHSSS represents the most relevant and appropriate quantitative data source that is available for addressing this topic. The limitations discussed above do not present strong enough challenges to suggest foregoing the current study all together.

CHAPTER 4

FINDINGS

I begin the analysis of the relationships between the timing of student and parent conversations and the outcomes of interest in this study by means of simple two-way comparisons. As shown in Table 4, which displays each dependent variable in the study broken down by the categories of *Parent Conversation,* early conversers were more likely than not to have taken advanced math classes in high school. The opposite was true for late conversers. Regardless of the timing of parent conversations, students were more likely than not to take four or more years of science. However, among late deciders the split was nearly even. Early timing appeared to have some connection to planning to major in a STEM field, with the percentage of those having such plans decreasing as the timing of conversations became later. Approximately one-quarter of early conversers reported such plans. This proportion decreased slightly among mid-level conversers. When considering late conversers only slightly less than a fifth expressed plans to major in a STEM field.

These comparisons offer some indication that earlier conversations with parents regarding what to do after high school are associated with taking advanced math classes in high school and perhaps to a lesser degree with taking four or more years of science and planning to major in a STEM field in college. However, the findings displayed in Table 4 do not account for the numerous other factors that may exert influence on these two outcomes. To take a more critical approach to investigating these relationships, I

Table 4: Dependent Variables by Timing of Earliest Parent Conversation

Parent Conversations	Advanced Math		Extra Science		STEM Major	
	No	Yes	No	Yes	No	Yes
7th grade or Before	39.4%	61.6%	35.8%	64.2%	75.8%	24.2%
8th or 9th Grade	49.5%	50.5%	43.1%	56.9%	80.0%	20..0%
After 9th or Never	54.9%	45.1%	48.3%	51.7%	81.5%	18.5%

Notes: Chi-square tests of independence revealed statistically significant differences by timing groups ($p<.001$) for all dependent variables.

have employed the probit regression techniques discussed earlier and have summarized the results in the tables below. To ease interpretation, when reporting models I have referred to first differences of the average marginal effects of independent binary factor variables and average marginal effects for the lone continuous variable, GPA. Embedded in all explanations of the models is the assumption that changes to the predicted probability of observing the outcome based on changes to independent variables are such when other variables in the model are held at their observed values. It should also be assumed that changes reflect what would be expected compared to the reference group for each variable.

Advanced Math Course Taking

Table 5 presents the results from the probit regression models predicting whether students took advanced math courses. Each model in this table included information from the entire sample of 6101 males and females as well as fixed effects for each of the high schools in the sample. In Model 1 I included only the primary predictor variables of

Table 5: Marginal Effects from Aggregate Probit Models for Advanced Math

	Model 1	Model 2	Model 3	Model 4
Parent Conversations				
7th grade or before	0.158***	0.048**	0.038**	0.035*
	(0.016)	(0.015)	(0.014)	(0.015)
8th or 9th grade	0.052**	0.005	-0.001	-0.004
	(0.017)	(0.012)	(0.013)	(0.013)
Female		-0.113***	-0.100***	-0.090***
		(0.010)	(0.010)	(0.010)
GPA		0.338***	0.319***	0.307***
		(0.015)	(0.015)	(0.015)
Underrepresented Minority		-0.054*	-0.040+	-0.039+
		(0.024)	(0.023)	(0.023)
Student Aspirations				
Bachelor's Degree		0.176***	0.161***	0.161***
		(0.017)	(0.017)	(0.017)
Graduate Degree		0.268***	0.248***	0.243***
		(0.022)	(0.023)	(0.023)
Undecided		0.175***	0.169***	0.168***
		(0.022)	(0.022)	(0.022)
Living Situation				
Live w/both parents			0.017	0.017
			(0.013)	(0.012)
Live w/other			-0.022	-0.024
			(0.030)	(0.029)
Family Income				
<$25,000			-0.049+	-0.053+
			(0.028)	(0.028)
$25,000 to $49,999			-0.052*	-0.052**
			(0.020)	(0.020)
$75,000 to $99,999			0.004	0.004
			(0.022)	(0.021)
$100,000 or more			0.026	0.024
			(0.024)	(0.024)
Don't know			-0.024	-0.023
			(0.019)	(0.019)
Parent Education				
One 4yr degree			0.032*	0.034*
			(0.014)	(0.014)
Both 4yr degrees			0.068***	0.068***
			(0.015)	(0.015)

Table 5 continued				
	Model 1	Model 2	Model 3	Model 4
Math Instruction				
Excellent				0.060***
				(0.013)
Unsatisfactory				-0.052**
				(0.016)
Not taught				-0.058*
				(0.029)
N	6101	6101	6101	6101
Log Likelihood Null	-4228.52	-4228.52	-4228.52	-4228.52
Log Likelihood Model	-4029.79	-3272.33	-3243.76	-3219.65
Pseudo R-Squared	0.05	0.23	0.23	0.24

Notes: Results reported as average marginal effect for GPA and marginal effects for discrete change of dummy variable from 0 to 1 for all other variables. Standard errors in parentheses and are clustered at the school level. Reference category for parent conversations is after 9th grade or never. Reference category for student aspirations is less than a four-year degree. Reference category for income is $50,000 to $75,000. Reference category for living situation is one parent. Reference category for parent education is no 4yr degrees. Reference category for math instruction is satisfactory. Models include fixed effects for high schools. Models also include categories for missing data for all variables except for Female, GPA, and Underrepresented Minority. + p<.10, * p<.05, **p<.01, *** p<.001

interest in an effort to establish whether the timing of parent conversations has even a baseline significant relationship to the outcome. These relationships were indeed significant, indicating that early conversers were 15.8 percentage points more likely to have taken advanced math courses compared to late conversers. Mid-level conversers experienced about one third of that advantage (5.2 percentage points).

In Model 2 I accounted for personal level characteristics of the students. Once controlling for these factors, mid-level conversers ceased to realize any higher probabilities of taking advanced math, and early conversers lost nearly two-thirds of their prior advantage. Based on this model, students' GPA and postsecondary aspirations exhibited the strongest associations with advanced math course taking. In sum, students aspiring to earn bachelor's degrees and graduate degrees, as well as those whose plans were undecided, were significantly more likely to be advanced math takers (.176, .268, and .175, respectively). Females in the sample were 11 percentage points less likely to take these courses. And on average, a one point increase in a student's GPA increased the probability of experiencing the outcome by a factor of .338. Finally, Model 2 showed a relatively weaker but significant negative relationship between the outcome variable and a student's status as an underrepresented minority.

Adding additional controls for students' family and background characteristics (Model 3) attenuates many of the relationships observed with conversation timing and personal factors from prior models. Few of these added family characteristics presented significant relations themselves, though. For example, there appears to be a small disadvantage for lower income levels, but only in the "25,000 to $49,999" category. Having two parents with a four-year degree, on the other hand, was associated with a small advantage in probability (0.06).

In the final model shown on Table 5, I included variables to control for students' satisfaction with their math instruction. These relationships presented themselves as expected, with positive experiences with instruction having a positive and significant relationship with taking advanced math classes and the opposite being true as well. In general, however, including these final controls did not substantively impact other predictors in the model.

Guided by suggestions in the literature, I next estimated the same models above based on the reduced subsamples of 2853 males and 3248 females. Tables 6 through 9 present the results from the respective probit regressions. For males, the findings indicated that only early conversers experienced an increased probability (15 percentage points) of taking advanced math classes, relative to late conversers. Both early and mid-

Table 6: Marginal Effects from Probit Models (by Gender) for Advanced Math: Conversations and fixed effects included

	Model 1 Aggregate	Model 5 Males Only	Model 6 Females Only
Parent Conversations			
7th or before	0.158***	0.151***	0.180***
	(0.016)	(0.025)	(0.022)
8th or 9th grade	0.052**	0.022	0.088***^
	(0.017)	(0.022)	(0.020)
N	6101	2853	3248
Log Likelihood Null	-4228.52	-1977.40	-2249.92
Log Likelihood Model	-4029.79	-1866.85	-2130.92
Pseudo R-Squared	0.05	0.06	0.05

Notes: Results reported as marginal effects for discrete change of dummy variable from 0 to 1. Standard errors in parentheses and are clustered at the school level in aggregate model. Reference category for parent conversations is after 9th grade or never. Models include fixed effects for high schools. Models also include category for missing data. + p<.10, * p<.05, ** p<.01, *** p<.001 ^ Denotes significant difference (p<.05) between male and female models.

level conversers in the female-only models have higher predicted probabilities, but only the marginal effect for mid-level conversers is significantly different between models (Table 6; Models 5 and 6).

I repeated the blocked regression approach from the aggregated models when examining relationships by gender. Early conversers in these models still realized a slight increase in probability of taking advanced math classes in both groups once personal characteristics had been accounted for (Table 7; Models 7 and 8). As with the full sample models, personal level factors presented strong relationships with the outcome in each subsample when added. For females, GPA had a significantly stronger positive relationship with the outcome than it did males by a factor of 12 percentage points. Postsecondary aspirations, on the other hand, mattered significantly more for males than females. Compared to those aspiring to earn less than a four-year degree, males planning

Table 7: Marginal Effects from Probit Models (by Gender) for Advanced Math: Conversation variables, personal characteristics, and fixed effects included

	Model 2 Aggregate	Model 7 Males Only	Model 8 Females Only
Parent Conversations			
7th grade or before	0.048**	0.048*	0.051*
	(0.015)	(0.023)	(0.020)
8th or 9th grade	0.005	-0.012	0.020
	(0.012)	(0.020)	(0.018)
Female	-0.113***		
	(0.010)		
GPA	0.338***	0.282***	0.401***^
	(0.015)	(0.015)	(0.015)
Underrepresented Minority	-0.054*	-0.026	-0.073*
	(0.024)	(0.032)	(0.031)
Student Aspirations			
Bach. Deg.	0.176***	0.217***	0.131***^
	(0.017)	(0.025)	(0.027)
Grad. Deg.	0.268***	0.301***	0.223***^
	(0.022)	(0.027)	(0.028)
Undecided	0.175***	0.188***	0.156***
	(0.022)	(0.034)	(0.035)
N	6101	2853	3248
Log Likelihood Null	-4228.52	-1977.40	-2249.92
Log Likelihood Model	-3272.33	-1524.24	-1711.17
Pseudo R-Squared	0.23	0.23	0.24

Notes: Results reported as average marginal effect for GPA and marginal effects for discrete change of dummy variable from 0 to 1 for all other variables. Standard errors in parentheses and are clustered at the school level in aggregate model. Reference category for parent conversations is after 9th grade or never. Reference category for student aspirations is less than a four-year degree. Models include fixed effects for high schools. Models also include categories for missing data for parent conversations and student aspirations. + p<.10, * p<.05, ** p<.01, *** p<.001. ^ Denotes significant differences (p<.05) between coefficients in male and female models.

to earn a graduate degree were 30 percent more likely to take advanced math courses. Females only saw a 22 percent increase for similar aspirations. The increased probability of taking advanced math for males aspiring to earn a bachelor's degree was noticeably higher than that for females as well (0.22 vs 0.13).

In Models 9 and 10 (Table 8) I included controls for family and background characteristics. Being an early decider in these models was associated with a four percent

Table 8: Marginal Effects from Probit Models (by Gender) for Advanced Math: Conversation variables, personal and background characteristics, and fixed effects included

		Model 2 Aggregate	Model 9 Males Only	Model 10 Females Only
Parent Conversations				
	7th or before	0.038**	0.040+	0.040*
		(0.014)	(0.023)	(0.020)
	8th or 9th Grade	-0.001	-0.016	0.013
		(0.013)	(0.019)	(0.018)
Female		-0.100***		
		(0.010)		
GPA		0.319***	0.267***	0.376***^
		(0.015)	(0.015)	(0.016)
Underrepresented Minority		-0.040+	-0.016	-0.056+
		(0.023)	(0.032)	(0.031)
Student Aspirations				
	Bach. Deg.	0.161***	0.205***	0.115***^
		(0.017)	(0.025)	(0.028)
	Grad. Deg.	0.248***	0.283***	0.203***^
		(0.023)	(0.027)	(0.029)
	Undecided	0.169***	0.185***	0.146***
		(0.022)	(0.034)	(0.035)
Living Situation				
	Live w/both parents	0.017	0.038	-0.004
		(0.013)	(0.024)	(0.021)
	Live w/other	-0.022	0.023	-0.049
		(0.030)	(0.047)	(0.039)
Family Income				
	<$25,000	-0.049+	-0.032	-0.062+
		(0.028)	(0.042)	(0.037)
	$25,000 to $49,999	-0.052*	-0.007	-0.091**^
		(0.020)	(0.030)	(0.029)
	$75,000 to $99,999	0.004	0.020	-0.008
		(0.022)	(0.028)	(0.029)
	$100,000 or more	0.026	0.008	0.047
		(0.024)	(0.028)	(0.030)
	Don't know	-0.024	-0.018	-0.028
		(0.019)	(0.025)	(0.024)
Parent Education				
	One 4yr degree	0.032*	0.030	0.027
		(0.014)	(0.021)	(0.019)
	Both 4yr degrees	0.068***	0.080***	0.057**
		(0.015)	(0.021)	(0.020)

Table 8 continued			
	Model 2 Aggregate	Model 9 Males Only	Model 10 Females Only
N	6101	2853	3248
Log Likelihood Null	-4228.52	-1977.40	-2249.92
Log Likelihood Null	-3243.76	-1510.95	-1691.23
Pseudo R-Squared	0.23	0.24	0.25

Notes: Results reported as average marginal effect for GPA and marginal effects for discrete change of dummy variable from 0 to 1 for all other variables. Standard errors in parentheses and are clustered at the school level in aggregate model. Reference category for parent conversations is after 9th grade or never. Reference category for student aspirations is less than four-year degree. Reference category for income is $50,000 to $75,000. Reference category for living situation is one parent. Reference category for parent education is no four-year degrees. Models include fixed effects for high schools. Models also include categories for missing data for all variables except for Female, GPA, and Underrepresented Minority. + p<.10, * p<.05, ** p<.01, *** p<.001. ^ Denotes significant differences between coefficients in disaggregated models.

advantage for females with regards to the probability of taking advanced math classes. However, though significant in its own model, this was not significantly different from the average effect for males. GPA remained a significant predictor for both males and females; however, the 38 percent increase for females was significantly greater than the 27 percent for males. All other aspiration levels for males and females were associated with higher predicted probability compared to peers aspiring to earn less than a bachelor's degree. Aspirations were again significantly stronger predictors for males than for females in disaggregated models. These models also yielded a stronger relationship for females regarding family income and advanced math course taking, with apparent negative associations at the lower income levels. Finally, both parents having at least a bachelor's degree was positively and significantly associated with the outcome for both males and females. Though, the relationships did not vary significantly by gender.

Turning to Table 9, I have included the final predictor variables for the advanced math models that account for students' satisfaction with their math instruction. Adding these final controls reduced the relationship of early conversations to only marginally significant levels (p<.10). GPA maintained its strong positive relationship with predicting whether a student took advanced math courses, and again showed a significantly stronger relationship for females. Males continued to realize stronger positive relationships between the outcome and their aspirations than did females; however, in this final set of models only the difference for bachelor's degree aspirations was significantly larger. Relationships and differences related to family income and student aspirations were relatively unchanged in this final model. In terms of classroom instruction variables, reporting that math instruction was excellent was associated with more than twice as strong an increase for males as for females (0.09 vs. 0.04, respectively), a difference that

Table 9: Marginal Effects from Probit Models (by Gender) for Advanced Math: Full models

	Model 4 Aggregate	Model 11 Males Only	Model 12 Females Only
Parent Conversations			
7th Grade or before	0.035* (0.015)	0.039+ (0.023)	0.037+ (0.020)
8th or 9th Grade	-0.004 (0.013)	-0.022 (0.019)	0.011 (0.018)
Female	-0.090*** (0.010)		
GPA	0.307*** (0.015)	0.255*** (0.015)	0.363***^ (0.016)
Underrepresented Minority	-0.039+ (0.023)	-0.016 (0.032)	-0.054+ (0.031)
Student Aspirations			
Bach. Deg.	0.161*** (0.017)	0.206*** (0.025)	0.114***^ (0.028)
Grad. Deg.	0.243*** (0.023)	0.274*** (0.027)	0.200*** (0.029)
Undecided	0.168*** (0.022)	0.183*** (0.034)	0.146*** (0.035)
Living Situation			
Live w/both parents	0.017 (0.012)	0.041+ (0.023)	-0.005 (0.021)
Live w/other	-0.024 (0.029)	0.024 (0.047)	-0.054 (0.038)
Family Income			
<$25,000	-0.053+ (0.028)	-0.035 (0.042)	-0.064+ (0.037)

Table 9 continued

	Model 4 Aggregate	Model 11 Males Only	Model 12 Females Only
Family Income			
$25,000 to $49,999	-0.052**	-0.006	-0.093**^
	(0.020)	(0.030)	(0.029)
$75,000 to $99,999	0.004	0.022	-0.011
	(0.021)	(0.028)	(0.029)
$100,000 or more	0.024	0.007	0.045
	(0.024)	(0.028)	(0.030)
Don't know	-0.023	-0.013	-0.032
	(0.019)	(0.025)	(0.024)
Parent Education			
One 4yr degree	0.034*	0.031	0.029
	(0.014)	(0.021)	(0.019)
Both 4yr degrees	0.068***	0.078***	0.058**
	(0.015)	(0.021)	(0.020)
Math Instruction			
Excellent	0.060***	0.088***	0.039*
	(0.013)	(0.019)	(0.019)
Unsatisfactory	-0.052**	-0.031	-0.063**
	(0.016)	(0.024)	(0.020)
Not taught	-0.058*	-0.028	-0.080*
	(0.029)	(0.042)	(0.038)
N	6101	2853	3248
Log Likelihood Null	-4228.52	-1977.40	-2249.92
Log Likelihood Model	-3219.65	-1496.12	-1679.78
Pseudo R-Squared	0.24	0.24	0.25

Notes: Results reported as average marginal effect for GPA and marginal effects for discrete change of dummy variable from 0 to 1 for all other variables. Standard errors in parentheses and are clustered at the school level in aggregate model. Reference category for parent conversations is after 9th grade or never. Reference category for student aspirations is less than a four-year degree. Reference category for income is $50,000 to $75,000. Reference category for living situation is one parent. Reference category for parent education is no 4yr degrees. Reference category for math instruction is satisfactory. Models include fixed effects for high schools. Models also include categories for missing data for all variables except for Female, GPA, and Underrepresented Minority. + p<.10, * p<.05, **p<.01, *** p<.001. ^ Denotes significant differences between coefficients in disaggregated models.

was also statistically significant. For females, having an unsatisfactory experience with math instruction was associated with a stronger negative relationship with advanced math course taking compared to males.

Taking Extra Science Courses

The second dependent variable explored in the study measured whether students reported having taken four or more years of science courses in high school. In estimating the associated models, I followed the same approach as when predicting advanced math taking. Table 10 displays the results for four models (Model 13- Model 16) that are fit using the full aggregate sample. Model 13 begins by accounting only for the timing of students' conversations regarding what to do after high school.[9] Specified in this way, the model estimated that early conversers had a 13 percentage point increased probability of taking four or more science classes, compared to late conversers. Mid-level conversers had slightly more than a third of that relative advantage.

Continuing to look at Table 10, adding controls for personal characteristics (Model 14) eliminated any statistically significant advantage for mid-level conversers and reduced that of early conversers by nearly three quarters. Being female was found to be associated with a slight but significant disadvantage relative to males while no differences were detected for underrepresented minorities. Students' GPA, as well as their postsecondary aspirations, however, were found to have highly significant and positive associations with predicting whether students took four or more science classes. For instance, a one point increase in GPA was associated with a 23 percentage point increase in the probability of experiencing the outcome, and aspirations of earning a graduate degree produced a similar relationship (.246).

In Model 15 I added factors related to students' family and background. Even the earliest conversations remained only marginally significant after this ($p<0.5$) and was

[9] Models also contain fixed effects for students' high school.

Table 10: Marginal Effects from Aggregate Probit Models for Extra Science

	Model 13	Model 14	Model 15	Model 16
Parent Conversations				
7th Grade or before	0.129***	0.039*	0.031+	0.024
	(0.015)	(0.016)	(0.017)	(0.016)
8th or 9th Grade	0.056***	0.014	0.008	0.003
	(0.016)	(0.016)	(0.016)	(0.016)
Female		-0.031**	-0.017	-0.003
		(0.012)	(0.012)	(0.012)
GPA		0.233***	0.217***	0.199***
		(0.012)	(0.013)	(0.012)
Underrepresented Minority		-0.019	-0.007	-0.001
		(0.022)	(0.023)	(0.022)
Student Aspirations				
Bach. Deg.		0.144***	0.131***	0.127***
		(0.021)	(0.019)	(0.020)
Grad. Deg.		0.246***	0.228***	0.213***
		(0.020)	(0.019)	(0.019)
Undecided		0.130***	0.125***	0.124***
		(0.024)	(0.024)	(0.025)
Living Situation				
Live w/both parents			0.013	0.009
			(0.017)	(0.016)
Live w/other			-0.028	-0.035
			(0.038)	(0.039)
Family Income				
<$25,000			-0.073*	-0.077**
			(0.029)	(0.028)
$25,000 to $49,999			-0.042+	-0.042+
			(0.022)	(0.022)
$75,000 to $99,999			-0.001	0.000
			(0.017)	(0.017)
$100,000 or more			0.010	0.008
			(0.026)	(0.025)
Don't know			-0.035+	-0.035+
			(0.019)	(0.018)
Parent Education				
One 4yr degree			0.030+	0.029+
			(0.016)	(0.015)
Both 4yr degrees			0.057**	0.056**
			(0.020)	(0.020)

Table 10 continued				
	Model 13	Model 14	Model 15	Model 16
Science Instruction				
Excellent				0.096***
				(0.015)
Unsatisfactory				-0.067***
				(0.018)
Not taught				-0.143***
				(0.030)
N	6101	6101	6101	6101
Log Likelihood Null	-4191.92	-4191.92	-4191.92	-4191.92
Log Likelihood Model	-3959.66	-3519.18	-3496.58	-3443.89
Pseudo R-Squared	0.05	0.16	0.17	0.18

Notes: Results reported as average marginal effect for GPA and marginal effects for discrete change of dummy variable from 0 to 1 for all other variables. Standard errors in parentheses and are clustered at the school level. Reference category for parent conversations is after 9th grade or never. Reference category for student aspirations is less than a four-year degree. Reference category for income is $50,000 to $75,000. Reference category for living situation is one parent. Reference category for parent education is no 4yr degrees. Reference category for science instruction is satisfactory. Models include fixed effects for high schools. Models also include categories for missing data for all variables except for Female, GPA, and Underrepresented Minority. + p<.10, * p<.05, ** p<.01, *** p<.001

only associated with a 3 percentage point increased probability. The significant negative association of being female ceased to exist in this model as well. Though slightly diminished in magnitude compared to the prior model, GPA and postsecondary aspirations still produced associations with taking four or more science classes that were all high in significance and magnitude relative to each factor's reference group. Of the newly included background and family variables, only the lowest level of family income (<$25,000) and having both parents with at least a four-year degree were found to be significant predictors, both positive as expected.

As a final step, in Model 16 I added controls for students experiences with classroom instruction in their science classes. At this point, no significant associations remained for either early or mid-level conversers. Female and underrepresented minority status also failed to present significant associations. GPA and students' aspirations, however, suffered only slight decreases in magnitude while retaining statistical significance. In all, even after adding all controls to the model, planning to earn a bachelor's degree was associated with a 13 percentage point increase in the probability of taking four or more science courses as opposed to aspiring to less than a four-year degree. Aspirations of earning a graduate degree were associated with more than a 20 percentage point increase compared to that same reference group. Students' experiences with science instruction exhibited relationships that were expected, with excellent experiences positively connected to the outcome and unsatisfactory experiences negatively so. Each were statistically significant.

After estimating these models using the full analytic sample, I repeated the same procedures for models that considered males and females separately. The conversations-only models (13, 17, and 18) shown in Table 11 display that, for males, only early conversers were significantly more likely to have taken four or more years of science compared to late conversers. Being a female early converser had a similarly significant relationship but with a smaller positive magnitude (.114 compared to .153).

Table 11: Marginal Effects from Probit Models (by Gender) for Extra Science: Conversations and fixed effects included

	Model 13 Aggregate	Model 17 Males Only	Model 18 Females Only
Parent Conversations			
7th or before	0.129*** (0.015)	0.153*** (0.025)	0.114*** (0.021)
8th or 9th grade	0.056*** (0.016)	0.014 (0.022)	0.089***^ (0.020)
N	6101	2853	3248
Log Likelihood Null	-4191.92	-1970.88	-2216.3368
Log Likelihood Model	-3959.66	-1850.64	-2077.54
Pseudo R-Squared	0.05	0.06	0.06

Notes: Results reported as marginal effects for discrete change of dummy variable from 0 to 1. Standard errors in parentheses and are clustered at the school level in aggregate model. Reference category for parent conversations is after 9th grade or never. Models include fixed effects for high schools. Models also include categories for missing data. + p<.10, * p<.05, ** p<.01, *** p<.001. ^ Denotes significant differences between coefficients in disaggregated models.

I also found, however, a significant relationship between taking more science classes and being a mid-level converser among females. The difference between male and female marginal effects for this fact was moderate (.075) and was significantly different.

Moving on to Table 12, Models 14, 19, and 20 show findings produced from introducing personal characteristics into the equations. Doing so appeared to mediate the significant relationships between conversation timing and science course taking for females. In the male only model (19) only being an early converser was positively and significantly associated with the outcome (seven percentage point increase). I also found that, at first glance, GPA was more strongly associated with taking more science classes for females than for males. The reverse was true for the positive associations with students' postsecondary aspirations. In particular, aspiring to earn a graduate degree for males was associated with an increased probability of 28 percentage points, compared to only a 22 percentage point increase for females. However, these marginal effects failed to meet the criteria needed to determine they were significantly different between models.

In Table 13, I present findings from models estimated after I added background and family characteristic controls. Introducing these variables resulted in only small changes to marginal effects of variables from the prior models. For males, however, being from the lowest family income group did present a rather large negative association with the outcome, suggesting that being in this group was connected to a 14 percentage point reduction in the probability of taking four or more science courses. This was a significantly different marginal effect than that found for females (-0.027). For both males and females, having two parents with at least a four-year degree was associated with about a six percentage point increase in the probability of experiencing the outcome.

Table 12: Marginal Effects from Probit Models (by Gender) for Extra Science: Conversation variables, personal characteristics, and fixed effects included

		Model 14 Aggregate	Model 19 Males Only	Model 20 Females Only
Parent Conversations				
	7th Grade or before	0.039*	0.072**	0.020
		(0.016)	(0.024)	(0.021)
	8th or 9th Grade	0.014	-0.014	0.036+
		(0.016)	(0.020)	(0.019)
Female		-0.031**		
		(0.012)		
GPA		0.233***	0.215***	0.249***
		(0.012)	(0.016)	(0.016)
Underrepresented Minority		-0.019	-0.034	0.003
		(0.022)	(0.033)	(0.032)
	Bachelor's Degree	0.144***	0.159***	0.123***
		(0.021)	(0.026)	(0.028)
	Graduate Degree	0.246***	0.279***	0.217***
		(0.020)	(0.028)	(0.029)
	Undecided	0.130***	0.155***	0.103**
		(0.024)	(0.035)	(0.035)
N		6101	2853	3248
Log Likelihood Null		-4191.92	-1970.88	-2216.34
Log Likelihood Model		-3519.18	-1616.14	-1867.97
Pseudo R-Squared		0.16	0.18	0.16

Notes: Results reported as average marginal effect for GPA and marginal effects for discrete change of dummy variable from 0 to 1 for all other variables. Standard errors in parentheses and are clustered at the school level in aggregate model. Reference category for parent conversations is after 9th grade or never. Reference category for student aspirations is less than a four-year degree. Models include fixed effects for high schools. Models also include categories for missing data. + p<.10, * p<.05, ** p<.01, *** p<.001.

The final models for predicting whether students took four or more years of science classes are shown in Table 14. Some evidence exists that early male conversers have an increased probability of taking four or more years of science courses relative to males that are late conversers. This held even after adding the final controls for students' experiences with science instruction, which were significant in almost every case for males and females. In general, I found that the associations between positive experiences

Table 13: Marginal Effects from Probit Models (by Gender) for Extra Science: Conversation variables, personal and background characteristics, and fixed effects included

	Model 15 Aggregate	Model 21 Males Only	Model 22 Females Only
Parent Conversations			
7th or before	0.031+	0.063**	0.012
	(0.017)	(0.024)	(0.021)
8th or 9th grade	0.008	-0.018	0.028
	(0.016)	(0.020)	(0.019)
Female	-0.017		
	(0.012)		
GPA	0.217***	0.204***	0.228***
	(0.013)	(0.016)	(0.017)
Underrepresented Minority	-0.007	-0.023	0.016
	(0.023)	(0.033)	(0.032)
Student Aspirations			
Bach. Deg.	0.131***	0.142***	0.108***
	(0.019)	(0.026)	(0.028)
Grad. Deg.	0.228***	0.258***	0.197***
	(0.019)	(0.028)	(0.029)
Undecided	0.125***	0.146***	0.097**
	(0.024)	(0.035)	(0.035)
Living Situation			
Live w/both parents	0.013	0.025	-0.002
	(0.017)	(0.024)	(0.022)
Live w/other	-0.028	0.023	-0.066+
	(0.038)	(0.049)	(0.039)
Family Income			
<$25,000	-0.073*	-0.143**	-0.027^
	(0.029)	(0.044)	(0.038)
$25,000 to $49,999	-0.042+	-0.016	-0.072*
	(0.022)	(0.031)	(0.030)
$75,000 to $99,999	-0.001	-0.002	0.002
	(0.017)	(0.029)	(0.031)
$100,000 or more	0.010	0.013	0.006
	(0.026)	(0.029)	(0.031)
Don't know	-0.035+	-0.017	-0.054*
	(0.019)	(0.026)	(0.025)
Parent Education			
One 4yr degree	0.030+	0.027	0.035+
	(0.016)	(0.022)	(0.020)
Both 4yr degrees	0.057**	0.057**	0.059**
	(0.020)	(0.022)	(0.021)

Table 13 continued			
	Model 15 Aggregate	Model 21 Males Only	Model 22 Females Only
N	6101	2853	3248
Log Likelihood Null	-4191.92	-1970.88	-2216.34
Log Likelihood Model	-3496.58	-1600.74	-1852.94
Pseudo R-Squared	0.17	0.19	0.16

Notes: Results reported as average marginal effect for GPA and marginal effects for discrete change of dummy variable from 0 to 1 for all other variables. Standard errors in parentheses and are clustered at the school level in aggregate model. Reference category for parent conversations is after 9th grade or never. Reference category for student aspirations is less than four-year degree. Reference category for income is \$50,000 to \$75,000. Reference category for living situation is one parent. Reference category for parent education is no four-year degrees. Reference category for parent expectation is attend 2-year/and transfer. Models include fixed effects for high schools. Models also include categories for missing data for all variables except for Female and Underrepresented Minority. + p<.10, * p<.05, ** p<.01, *** p<.001. ^ Denotes significant differences between coefficients in disaggregated models.

and increased probabilities of taking four or more years of science were stronger for females, as were negative experiences and decreased probabilities. None of these effects, however, differed significantly between the two disaggregated models. In fact, after all independent variables were accounted for in the models, only the association with being in the lowest income group (<\$25,000) presented marginal effects that differed significantly across models disaggregated by gender.

Planning to Major in a STEM Field

Turning to the final dependent variable, whether a student expressed a plan to major in a STEM field in college, I departed slightly from the blocked method used in previous models. As can be seen in Table 15, I first controlled only for the timing of student and parent conversations about what to do after high school. The results for this model (25) revealed a significant relationship only for early conversers, whose conversations were connected to a six percentage point increase in the probability of planning to major in STEM in the aggregate sample.

Table 14: Marginal Effects from Probit Models (by Gender) for Extra Science: Full models

	Model 16 Aggregate	Model 23 Males Only	Model 24 Females Only
Parent Conversations			
7th Grade or before	0.024 (0.016)	0.058* (0.024)	0.002 (0.021)
8th or 9th Grade	0.003 (0.016)	-0.025 (0.020)	0.025 (0.018)
Female	-0.003 (0.012)		
GPA	0.199*** (0.012)	0.190*** (0.016)	0.204*** (0.017)
Underrepresented Minority	-0.001 (0.022)	-0.019 (0.033)	0.025 (0.032)
Student Aspirations			
Bachelor's Degree	0.127*** (0.020)	0.140*** (0.026)	0.101*** (0.028)
Grad. Deg.	0.213*** (0.019)	0.246*** (0.028)	0.179*** (0.029)
Undecided	0.124*** (0.025)	0.143*** (0.035)	0.095** (0.035)
Living Situation			
Live w/both parents	0.009 (0.016)	0.024 (0.024)	-0.008 (0.021)
Live w/other	-0.035 (0.039)	0.019 (0.049)	-0.078* (0.039)
Family Income			
<$25,000	-0.077** (0.028)	-0.146*** (0.044)	-0.032^ (0.037)
$25,000 to $49,999	-0.042+ (0.022)	-0.019 (0.030)	-0.071* (0.030)
$75,000 to $99,999	0.000 (0.017)	-0.003 (0.029)	0.005 (0.031)
$100,000 or more	0.008 (0.025)	0.009 (0.029)	0.005 (0.031)
Don't know	-0.035+ (0.018)	-0.021 (0.026)	-0.050* (0.024)
Parent Education			
One 4yr degree	0.029+ (0.015)	0.028 (0.021)	0.034+ (0.020)
Both 4yr degrees	0.056** (0.020)	0.055* (0.022)	0.061** (0.021)

Table 14 continued				
		Model 16 Aggregate	Model 23 Males Only	Model 24 Females Only
Science Instruction				
	Excellent	0.096***	0.087***	0.110***
		(0.015)	(0.020)	(0.020)
	Unsatisfactory	-0.067***	-0.034	-0.093***
		(0.018)	(0.025)	(0.021)
	Not taught	-0.143***	-0.131**	-0.161***
		(0.030)	(0.047)	(0.044)
N		6101	2853	3248
Log Likelihood Null		-4191.92	-1970.88	-2216.34
Log Likelihood Model		-3443.89	-1583.00	-1813.29
Pseudo R-Squared		0.18	0.20	0.18

Notes: Results reported as average marginal effect for GPA and marginal effects for discrete change of dummy variable from 0 to 1 for all other variables. Standard errors in parentheses and are clustered at the school level in aggregate model. Reference category for parent conversations is after 9th grade or never. Reference category for student aspirations is less than a four-year degree. Reference category for income is $50,000 to $75,000. Reference category for living situation is one parent. Reference category for parent education is no 4yr degrees. Reference category for science instruction is satisfactory. Models include fixed effects for high schools. Models also include categories for missing data for all variables except for Female, GPA, and Underrepresented Minority. + p<.10, * p<.05, ** p<.01, *** p<.001. ^ Denotes significant differences between coefficients in disaggregated models.

Given the significant relationships between the timing of student and parent conversations and the prior two dependent variables explored in the study, I decided to include those (along with related classroom satisfaction controls) as the next step in the models predicting STEM.

Including these controls appeared to have eliminated the significance of the relationship observed in the prior model for early conversers. Both advanced math and taking four or five years of science were significant with magnitudes of .105 and .098, respectively. Expressing that instruction was excellent was positively and significantly associated with majoring in STEM for math, science, and technology classes, though the magnitude was strongest for science. Unsatisfactory experiences only reached statistically significant levels for science, however, with those students experiencing a 4.8 percentage point decrease in the probability of experiencing the outcome.

Table 15: Marginal Effects from Aggregate Probit Models for STEM

	Model 25	Model 26	Model 27	Model 28
Parent Conversations				
7th Grade or before	0.058***	0.014	0.000	0.001
	(0.014)	(0.013)	(0.013)	(0.013)
8th or 9th Grade	0.014	-0.001	-0.007	-0.007
	(0.012)	(0.012)	(0.013)	(0.013)
Advanced Math		0.105***	0.050***	0.049***
		(0.009)	(0.012)	(0.011)
Extra Science		0.098***	0.066***	0.066***
		(0.012)	(0.012)	(0.012)
Math Instruction				
Excellent		0.036*	0.027+	0.028+
		(0.016)	(0.015)	(0.015)
Unsatisfactory		-0.008	-0.006	-0.005
		(0.013)	(0.013)	(0.013)
Not taught		0.067+	0.076+	0.076+
		(0.041)	(0.043)	(0.043)
Science Instruction				
Excellent		0.048**	0.037*	0.035*
		(0.017)	(0.015)	(0.015)
Unsatisfactory		-0.048***	-0.041**	-0.042**
		(0.013)	(0.013)	(0.013)
Not taught		-0.061*	-0.052	-0.053
		(0.031)	(0.035)	(0.035)
Technology Instruction				
Excellent		0.027*	0.015	0.017
		(0.012)	(0.013)	(0.013)
Unsatisfactory		-0.000	-0.000	0.001
		(0.020)	(0.020)	(0.020)
Not taught		-0.022	-0.030	-0.029
		(0.023)	(0.023)	(0.023)
Female			-0.087***	-0.087***
			(0.010)	(0.011)
GPA			0.074***	0.071***
			(0.013)	(0.012)
Underrepresented Minority			-0.009	-0.008
			(0.021)	(0.022)
Student Aspirations				
Bach. Deg.			0.057***	0.057***
			(0.015)	(0.015)

Table 15 continued				
	Model 25	Model 26	Model 27	Model 28
Student Aspirations				
Grad. Deg.			0.129***	0.127***
			(0.013)	(0.014)
Undecided			0.023	0.023
			(0.018)	(0.018)
Living Situation				
Live w/both parents				0.011
				(0.018)
Live w/other				-0.023
				(0.026)
Family Income				
<$25,000				0.030
				(0.035)
$25,000 to $49,999				-0.002
				(0.023)
$75,000 to $99,999				0.011
				(0.019)
$100,000 or more				-0.021
				(0.016)
Don't know				-0.002
				(0.015)
Parent Education				
One 4yr degree				-0.010
				(0.014)
Both 4yr degrees				0.019
				(0.016)
N	6101	6101	6101	6101
Log Likelihood Null	-3017.69	-3017.69	-3017.69	-3017.69
Log Likelihood Model	-2961.86	-2738.61	-2639.60	-2631.49
Pseudo R-Squared	0.02	0.09	0.13	0.13

Notes: Results reported as average marginal effect for GPA and marginal effects for discrete change of dummy variable from 0 to 1 for all other variables. Standard errors in parentheses and are clustered at the school level. Reference category for parent conversations is after 9th grade or never. Reference category for student aspirations is less than four-year degree. Reference category for income is $50,000 to $75,000. Reference category for living situation is one parent. Reference category for parent education is no four-year degrees. Reference category for math/science/tech instruction is satisfactory. Models include fixed effects for high schools. Models also include categories for missing data for all variables except for Female, GPA, and Underrepresented Minority. + p<.10, * p<.05, ** p<.01, *** p<.001.

In Model 27 I accounted for students' personal characteristics as well. As with models concerning the other two dependent variables in the study, being female was significantly and negatively associated with experiencing the outcome. GPA and student aspirations were also found to be positive and significant. A one point increase in GPA, for example, was associated with an average increase of just over seven percentage points in terms of the probability for majoring in STEM. Aspiring to earn a bachelor's degree was found to have a slightly smaller magnitude (.057); however, planning to earn a graduate degree was associated with a 13 percentage point increase in the chances of planning to major in STEM. Adding these controls to the model also appeared to mediate the relationships between students' classroom instruction experiences related to math and technology. Science instruction factors for excellent and unsatisfactory retained their significant relationships. Both were somewhat diminished, though.

As a final step in attempting to predict students' plans whether to major in a STEM field in college, I added the controls for family and background characteristics (Model 28). Doing so had very little impact on the model itself. None of the marginal effects for indicators used in Models 25-27 changed by more than three-tenths of a percentage point. The fact that nothing seemed to change suggests that adding these controls is likely unnecessary.

Although I altered the order in which I introduced factors into the models predicting majoring in a STEM field, I took the same approach of re-estimating each of the models disaggregated by gender. As shown in Table 16, in the base model I found that for males, only being an early converser was associated with a higher probability of majoring in STEM field (5.8 percentage point increase). This association was about 3 percentage points larger for females, and was found to have a higher significance level. And whereas no connection was found for males that were mid-level conversers, in the female-only model, this timing was associated with a significant 4 percentage point increase in the probability of majoring in STEM. However, follow-up tests revealed that neither of these differences between models was statistically significant.

Table 16: Marginal Effects from Probit Models (by Gender) for STEM: Conversations and fixed effects included

	Model 25 Aggregate	Model 29 Males Only	Model 30 Females Only
Parent Conversations			
7th or before	0.058***	0.054*	0.083***
	(0.014)	(0.024)	(0.018)
8th or 9th grade	0.014	0.000	0.041**
	(0.012)	(0.020)	(0.019)
N	6101	2853	3248
Log Likelihood Null	-3017.69	-1555.05	-1436.84
Log Likelihood Model	-2961.86	-1504.45	--1392.85
Pseudo R-Squared	0.02	0.03	0.03

Notes: Results reported as average marginal effect for GPA and marginal effects for discrete change of dummy variable from 0 to 1 for all other variables. Standard errors in parentheses and are clustered at the school level in aggregate model. Reference category for parent conversations is after 9th grade or never. Reference category for student aspirations is less than a four-year degree. Models include fixed effects for high schools. Models also include categories for missing data. + p<.10, * p<.05, ** p<.01, *** p<.001.

In Table 17 I display the findings that arose from adding additional controls for students' course taking behaviors and classroom experiences. For males, variables related to parent conversations lost all significant relationships with planning to major in STEM. Taking advanced math courses, on the other hand, was a strong and significant predictor of the outcome, as was taking four or more science classes. Though both course taking behaviors held this association, only males' excellent and unsatisfactory experiences with math instruction were significantly related to the outcome and in expected directions. Regarding females, being an early converser maintained a significant positive connection with a student's plans to major in STEM in college. Both course taking behaviors were

Table 17: Marginal Effects from Probit Models (by Gender) for STEM: Conversations, classroom variables, and fixed effects included

	Model 26 Aggregate	Model 31 Males Only	Model 32 Females Only
Parent Conversations			
7th Grade or before	0.014	-0.004	0.049**^
	(0.013)	(0.021)	(0.017)
8th or 9th Grade	-0.001	-0.017	0.026+
	(0.012)	(0.018)	(0.015)
Advanced Math	0.105***	0.156***	0.052***^
	(0.009)	(0.016)	(0.014)
Extra Science	0.098***	0.116***	0.086***
	(0.012)	(0.016)	(0.015)
Math Instruction			
Excellent	0.036*	0.078***	-0.013^
	(0.016)	(0.024)	(0.018)
Math Instruction			
Unsatisfactory	-0.008	-0.048*	0.020^
	(0.013)	(0.023)	(0.020)
Not taught	0.067+	0.026	0.096+
	(0.041)	(0.052)	(0.050)
Science Instruction			
Excellent	0.048**	0.019	0.073**
	(0.017)	(0.023)	(0.023)
Science Instruction			
Unsatisfactory	-0.048***	-0.038	-0.049**
	(0.013)	(0.024)	(0.017)
Not taught	-0.061*	-0.021	-0.081**
	(0.031)	(0.054)	(0.031)
Technology Instruction			
Excellent	0.027*	0.037+	0.010
	(0.012)	(0.020)	(0.017)
Unsatisfactory	-0.000	0.000	-0.002
	(0.020)	(0.033)	(0.024)
Not taught	-0.022	-0.067	0.013
	(0.023)	(0.046)	(0.037)
N	6101	2853	3248
Log Likelihood Null	-3017.69	-1555.05	-1436.84
Log Likelihood Model	-2738.61	-1331.68	-1327.46
Pseudo R-Squared	0.09	0.14	0.08

Notes: Results reported as average marginal effect for GPA and marginal effects for discrete change of dummy variable from 0 to 1 for all other variables. Standard errors in parentheses and are clustered at the school level in aggregate model. Reference category for parent conversations is after 9th grade or never. Reference category for math/science/tech instruction is satisfactory. Models include fixed effects for high schools. Models also include categories for missing data. + p<.10, * p<.05, ** p<.01, *** p<.001.
^ Denotes significant differences between coefficients in disaggregated models.

also positively associated with the outcome for females as well but with less magnitude. In fact the five percentage point increase in probability associated with females taking advanced math in high school was only one third of that seen for males, a difference that was statistically significant between the models. The associations between female's math instruction experiences were also significantly lower than males, with none of those factors achieving statistically significant levels in female-only models. All science instruction variables, on the other hand, resulted in significant associations for females. Though none were significant in male models, the differences between disaggregated samples were not large enough to be considered significant between the two.

Introducing controls for students' personal characteristics presented a number of changes that can be seen on Table 18. First, these controls appear to have mediated significant relationships and magnitudes for the timing of parent conversations in models for both males and females. Similarly, personal characteristics seemed to noticeably attenuate the associations between students' course taking behaviors and their plans to major in STEM. For males, the magnitude for taking advanced math class decreased from .156 in the previous model to .097 in Model 33, and the discrete change for taking four or five years of science classes fell from .116 to .071. Each remained a significant predictor, though. For females, while both course taking behaviors also experienced a drop in magnitude, only taking extra science courses remained a significant predictor of a six percentage point increase in the probability of majoring in a STEM field. And as with the prior model, the difference between the male and female marginal effects for taking advanced math courses was statistically significant. In terms of classroom instruction, the patterns discussed above remained the same for the most part after accounting for personal characteristics. Math instruction was associated more with majoring in STEM for males and the opposite was true for science instruction. Though, only the association

Table 18: Marginal Effects from Probit Models (by Gender) for STEM: Conversations, classroom variables, and fixed effects included

	Model 27 Aggregate	Model 33 Males Only	Model 34 Females Only
Parent Conversations			
7th Grade or before	0.000 (0.013)	-0.025 (0.020)	0.021 (0.017)
8th or 9th Grade	-0.007 (0.013)	-0.026 (0.017)	0.011 (0.015)
Advanced Math	0.050*** (0.012)	0.097*** (0.017)	0.011^ (0.015)
Extra Science	0.066*** (0.012)	0.071*** (0.017)	0.062*** (0.015)
Math Instruction			
Excellent	0.027+ (0.015)	0.072** (0.023)	-0.015^ (0.018)
Unsatisfactory	-0.006 (0.013)	-0.041+ (0.023)	0.017 (0.019)
Not taught	0.076+ (0.043)	0.028 (0.051)	0.101* (0.049)
Science Instruction			
Excellent	0.037* (0.015)	0.014 (0.023)	0.058* (0.022)
Unsatisfactory	-0.041** (0.013)	-0.036 (0.024)	-0.040* (0.017)
Science Instruction			
Not taught	-0.052 (0.035)	0.001 (0.056)	-0.073* (0.033)
Technology Instruction			
Excellent	0.015 (0.013)	0.026 (0.020)	0.009 (0.017)
Unsatisfactory	-0.000 (0.020)	-0.001 (0.032)	-0.005 (0.024)
Not taught	-0.030 (0.023)	-0.079+ (0.044)	0.001 (0.035)
Female	-0.087*** (0.010)		
GPA	0.074*** (0.013)	0.102*** (0.017)	0.046**^ (0.017)

Table 18 continued

		Model 27 Aggregate	Model 33 Males Only	Model 34 Females Only
Underrepresented Minority		-0.009	-0.004	-0.019
		(0.021)	(0.031)	(0.027)
Student Aspirations				
	Bach. Deg.	0.057***	0.066**	0.040*
		(0.015)	(0.022)	(0.018)
	Grad. Deg.	0.129***	0.102***	0.136***
		(0.013)	(0.025)	(0.020)
	Undecided	0.023	-0.012	0.045+
		(0.018)	(0.028)	(0.024)
N		6101	2853	3248
Log Likelihood Null		-3017.69	-1555.05	-1436.84
Log Likelihood Model		-2639.60	-1287.78	-1228.78
Pseudo R-Squared		0.13	0.17	0.10

Notes: Results reported as average marginal effect for GPA and marginal effects for discrete change of dummy variable from 0 to 1 for all other variables. Standard errors in parentheses and are clustered at the school level in aggregate model. Reference category for parent conversations is after 9th grade or never. Reference category for math/science/tech instruction is satisfactory. Reference category for student aspirations is less than a four-year degree. Models include fixed effects for high schools. Models also include categories for missing data for all variables except female, GPA, and underrepresented minority. + p<.10, * p<.05, ** p<.01, *** p<.001. ^ Denotes significant differences between coefficients in disaggregated models.

with an excellent rating for math instruction was significantly different across models. In terms of the personal characteristics themselves, for males, GPA had a significantly stronger positive relationship with students' plans to major in a STEM field. Among females, bachelor's degree aspirers seemed to have less an advantage relative to those aspiring to less than four-year degrees than did males and more of an advantage than males for those aspiring to graduate degrees. These differences were not significant, however.

Table 19 shows that, as with the aggregated sample, nearly all the relationships observed in Models 33 and 34 remained essentially unaltered after adding controls for background and family characteristics in Models 35 and 36. In fact, the largest change observed was the reduction of the association for female's GPAs and plans to major in

STEM from a factor of .046 (Model 34) to a factor of .037. The lack of significant relationships among these controls once again suggests that they are likely superfluous to these predictive models.

Table 19: Marginal Effects from Probit Models (by Gender) for STEM: Full models

		Model 28 Aggregate	Model 35 Males Only	Model 36 Females Only
Parent Conversations				
	7th or before	0.001 (0.013)	-0.021 (0.020)	0.021 (0.017)
	8th or 9th grade	-0.007 (0.013)	-0.022 (0.018)	0.009 (0.015)
Advanced Math		0.049*** (0.011)	0.098*** (0.017)	0.011^ (0.015)
Extra Science		0.066*** (0.012)	0.073*** (0.017)	0.062*** (0.015)
Math Instruction				
	Excellent	0.028+ (0.015)	0.073** (0.023)	-0.015^ (0.018)
	Unsatisfactory	-0.005 (0.013)	-0.038 (0.023)	0.017 (0.020)
	Not taught	0.076+ (0.043)	0.030 (0.051)	0.097+ (0.049)
Science Instruction				
	Excellent	0.035* (0.015)	0.012 (0.023)	0.058** (0.022)
	Unsatisfactory	-0.042** (0.013)	-0.035 (0.024)	-0.042* (0.017)
	Not taught	-0.053 (0.035)	-0.003 (0.055)	-0.074* (0.033)
Technology Instruction				
	Excellent	0.017 (0.013)	0.028 (0.020)	0.010 (0.017)
	Unsatisfactory	0.001 (0.020)	-0.003 (0.032)	-0.004 (0.024)
	Not taught	-0.029 (0.023)	-0.074+ (0.045)	0.002 (0.035)
Female		-0.087*** (0.011)		
GPA		0.071*** (0.012)	0.101*** (0.018)	0.037*^ (0.017)

Table 19 continued			
	Model 28 Aggregate	Model 35 Males Only	Model 36 Females Only
Underrepresented Minority	-0.008	-0.003	-0.015
	(0.022)	(0.031)	(0.028)
Student Aspirations			
Bach. Deg.	0.057***	0.067**	0.035+
	(0.015)	(0.022)	(0.019)
Grad. Deg.	0.127***	0.102***	0.130***
	(0.014)	(0.025)	(0.021)
Undecided	0.023	-0.013	0.043+
	(0.018)	(0.028)	(0.025)
Living Situation			
Live w/both parents	0.011	0.003	0.025
	(0.018)	(0.022)	(0.017)
Live w/other	-0.023	0.024	-0.047
	(0.026)	(0.048)	(0.028)
Family Income			
<$25,000	0.030	0.035	0.031
	(0.035)	(0.041)	(0.032)
$25,000 to $49,999	-0.002	-0.033	0.034
	(0.023)	(0.027)	(0.024)
$75,000 to $99,999	0.011	-0.011	0.046+
	(0.019)	(0.026)	(0.024)
$100,000 or more	-0.021	-0.042+	0.008
	(0.016)	(0.024)	(0.022)
Don't know	-0.002	-0.002	0.011
	(0.015)	(0.023)	(0.019)
Parent Education			
One 4yr degree	-0.010	-0.020	0.003
	(0.014)	(0.019)	(0.016)
Both 4yr degrees	0.019	0.025	0.016
	(0.016)	(0.019)	(0.017)
N	6101	2853	3235
Log Likelihood Null	-3017.69	-1555.05	-1434.54
Log Likelihood Model	-2631.49	-1281.41	-1278.38
Pseudo R-Squared	0.13	0.18	0.11

Notes: Results reported as average marginal effect for GPA and marginal effects for discrete change of dummy variable from 0 to 1 for all other variables. Standard errors in parentheses and are clustered at the school level in aggregate model. Reference category for parent conversations is after 9th grade or never. Reference category for student aspirations is less than four-year degree. Reference category for income is $50,000 to $75,000. Reference category for living situation is one parent. Reference category for parent education is no four-year degrees. Reference category for math/science/tech instruction is satisfactory. Models include fixed effects for high schools. Models also include categories for missing data for all variables except for Female, GPA, and Underrepresented Minority. + p<.10, * p<.05, ** p<.01, *** p<.001. ^ Denotes significant differences between coefficients in disaggregated models.

CHAPTER 5

DISCUSSION AND CONCLUSION

In this study I focused on the possible connections between the timing of students' earliest conversations with their parents about what to do after high school and three important STEM Pipeline outcomes: taking advanced math courses in high school, taking four or more years of science courses in high school, and planning to major in a STEM field in college. Findings from the analytic models investigating these relationships yielded mixed results. After controlling for a number of students' academic, personal, and background characteristics, there is some evidence that beginning student-parent conversations before the eighth grade is associated with higher probabilities of taking advanced math courses in high school. The same cannot be said for taking extra years of science classes. Once all other factors had been taken into account, the early significant relationships detected between conversation timing and science course taking were explained away. Similar findings emerged through the process of determining whether earlier conversations about what to do after high school were significantly associated with predicting higher probabilities of planning to major in a STEM field. Although basic models seemed to indicate such was the case, the significant relationships disappeared once all controls had been added.

As a second point of focus in this study, I explored whether estimating models disaggregated by gender would yield results that support theoretical implications from the research that males and females have very different experiences in the STEM pipeline

(Eccles, 1987). Findings from the gender-specific models also produced mixed results. For all three dependent variables, slight differences emerged between males and females connected to associations of the timing of student and parent conversations and the outcomes of interest. However, once all controls had been added to the full models, no significant relationships remained for either gender. In other cases, some factors emerged as significant predictors for one gender but not for another. For example, in models predicting whether a student took advanced math courses in high school, reporting that math instruction had been "unsatisfactory" was associated with a statistically significant six percentage point decrease in the probability of experiencing the outcome for females. For males, the relationship could not be said to be different from zero. Although these seemed to provide support for the argument of different and gendered pathways, additional tests for significance failed to establish that the differences between models were non-zero. Complicating matters further, in some cases I did find significant differences between the marginal effects observed for males and females. For instance, among males, taking advanced math courses in high school was associated with a 10 percentage point increase in the probability of planning to major in a STEM field in college whereas no such advantage was determined to be significant for females in the study.

Taken together, these stories fail to point to clear implications concerning how the timing of student and parent conversations about what to do after high school might be connected to the outcomes of interest in this study. Nevertheless, they do establish some starting points for conversation. For instance, for all dependent variables, being an early converser was associated in the base models with significantly increased probabilities of experiencing the outcome relative to late conversers. Mid-level conversers also saw significant increases in probability of taking advanced math or extra science courses in high school in those models. Thus, it can be argued that some connection exists between talking to students early about life after high school and their behaviors related to a number of STEM-relevant outcomes.

These relationships, however, may likely be expressed through other influential factors. For instance, in the full models, being an early converser was significantly associated with only one outcome of interest: taking advanced math courses. This result seems reasonable in that, of all the outcomes, the sequential nature of mathematics courses makes this variable the most reasonably susceptible to the influence of timing. It may also be the case that the timing of conversations expresses an influence through other important variables accounted for in the models. In prior work with my colleagues (Harding et al., 2017), we demonstrated that early information about college was significantly associated with students' postsecondary aspirations. Given that student aspirations were included as personal characteristics in this study as well, it may be the case that the connections between early conversations with parents and the outcomes of interest in this study are explained through the relationship of timing and postsecondary aspirations. This argument is supported in part by the findings that students' aspirations remain strong and significant predictors of advanced math and extra science course taking, as well as planning to major in a STEM field, in nearly all models in the study, aggregate and disaggregate alike. The same is true for GPA. In other words, students that begin conversations with their parents early regarding what to do after high school may be motivated or encouraged to achieve higher grades and plan to go further in college than those who begin such conversations later, when they may lack sufficient time to react and establish strong habits. Such causal inferences, though appealing, are not identifiable in this study.

In this study I also attempted to determine whether the findings might support arguments from the literature that males and females have very different experiences in the STEM pipeline, so much so that it justifies estimating separate statistical models by gender. Though results from the statistical models are conflicting, I believe there exists enough reason to, at the very least, follow a similar approach in other studies related to the STEM pipeline. With many of the models in this study, estimating based on samples disaggregated by gender frequently led to substantively different inferences. For example, all else equal, positive math instructional experiences seemed to matter more for males in the study whereas negative experiences mattered more for females. For females, all science classroom instruction experiences yielded stronger relationships with taking four or more years of science than they did for males. However, taking advanced math classes in high school was a much stronger predictor of a student planning to major in a STEM field for males than for females. And while math instruction experiences were only significantly associated with planning to major in a STEM field for males, the opposite was the case for experiences with science instruction.

Of course, as mentioned above, not all of the differences observed between gender-disaggregated models held up to the added scrutiny of tests for statistical differences. And there is no simple solution for deciding which findings should carry the most weight. Using the most conservative restrictions, one could argue that the relatively small number of significant differences by gender do not support the notion that the experiences of males and females in the STEM pipeline vary so greatly that separate models are required. Though this makes for a somewhat compelling argument, there is some substantive evidence that suggests otherwise. For example, models predicting both advanced math course taking and plans to major in a STEM field yielded a number of differences related to students' classroom instruction experiences that, despite not being significant between samples, do align to prior literature and merit some attention. particularly regarding how these experiences tend to be more negative for females (Cordova-Wentling & Camacho, 2006; Hazari et al., 2007; Osborne et al., 2003, Riegle-Crumb & Moore, 2013). Though not the focus of this study, findings related to these factors provide some corroborating evidence of a gender-varying relationship between classroom-related variables and STEM pipeline outcomes.

These results presented and discussed herein give rise to a number of implications for practice and possibly for policy. First, though modest, the positive and significant association between being an early converser and taking advanced math courses in high school suggests that students may in fact benefit from discussing postsecondary plans even earlier than is traditionally called for by the literature. As these data indicate, these types of conversations may be beneficial even as early as when students are in elementary school. Beginning conversations at this age allows students sufficient time to make decisions about attending college (Harding et al., 2017) and then to make appropriate decisions about course work as they grow older and move through middle school and on into high school. If students are prepared for introductory algebra in the seventh grade, for instance, they should be prepared for later work throughout the sequence of other more advanced courses in mathematics (Adelman, 2006).

Improvements in this area would be welcomed by a number of groups focused on educational equity. Achieve Inc. (2008), for example has suggested that all students should take four years of math in high school, culminating in at least Algebra II or its equivalent. These classes, along with those that go beyond them in content, the organization argues, are vital to ensuring access to postsecondary education and can only be reached if students begin taking Algebra I early on. This belief has become so strong among certain groups and in even certain cities and states that policymakers have pushed forward an agenda that has come to be known as the Algebra for All movement.

In 1997, for example, Chicago Public Schools implemented a policy that eliminated remedial coursework across high school subject areas and required all ninth-grade students to take Algebra and then Geometry and Algebra II in subsequent years (Nomi, 2012). A year later, California also began attempts to increase early algebra taking by penalizing middle schools that enrolled eighth-graders in pre-algebra classes. Similarly, by 2008, the California State Board of Education had made the Algebra California Standards Test the "sole test of record," linking eighth-grade students' proficiency requirements under the *No Child Left Behind Act* to Algebra I competencies (Domina, McEachin, Penner, & Penner, 2015). Though the approach was later eschewed in California in favor of the Common Core State Standards, these examples of broad-scale algebra-for-all policies represent the strength of the appeal of practices and measures that ensure all students have access to these building-block courses and foundational materials as soon as possible.

The Algebra-for-All movement is not without its critics, however. As Tom Loveless of the Brookings Brown Center on Education Policy has suggested, "The push for universal eighth-grade algebra is based on an argument for equity, not on empirical evidence" (2007, p. 3). Findings from the Chicago Public Schools policy mentioned above, for example, suggested that the practice had adverse affects on the math test scores of previously high-achieving students that the authors attribute to the resulting increased variation in student ability observed in Algebra I classes once the subject became required for all students (Nomi, 2012). Domina et al. (2015) found that curricular intensification resulting from the algebra-for-all policies in California led, on average, to negative effects on student test scores for students in large districts. Clotfelter et al. (2013, 2015) have found similarly disappointing evidence based on data from two large school districts in North Carolina.

This debate surrounding the algebra-for-all movement complicates the issue of drawing implications from the findings of this study. The significant associations found herein between early student and parent conversations and advanced math course taking in high school imply that parents should begin talking to their children very early regarding what to do after high school. The strong relationships of parent-education and students' advanced math course taking also suggest that students whose parents did not go to college may even need to have these conversations with teachers or school counselors as well (or instead), a notion certainly supported by prior research (Bell, Rowan-Kenyon, & Perna, 2010; Bonous-Hammarth & Allen, 2005; Harding et al., 2017). One might argue, however, that given the evidence that taking Algebra early on, and especially when unprepared, might be detrimental to a number of students, policy makers and practitioners should avoid pushing for increased participation altogether.

I believe, though, that the results from this study may not be entirely susceptible to such criticism. The negative effects associated with Algebra-for-All policies have thus far been shown to apply to students in areas where early algebra course taking was perhaps prematurely imposed. By subjecting students to mathematical concepts and principals before they were ready, cities, districts, and states may have inadvertently discouraged some students from following a course trajectory that would allow them to enroll in and succeed in advanced math courses in high school. By engaging students in conversations about what to do after high school at an early age, however, parents and educators might give younger students the information they need to make decisions about beginning Algebra I at an early enough stage to enable them to take advanced math courses in subsequent years. In this way, participation in middle school Algebra, and more complex courses later, might be increased through more-informed self-selection rather than through policies of curricular coercion. What is more, implementing such an approach would come at very little expense as it would only require the dissemination of information to students at an earlier age.

This study ultimately was focused not just on advanced math course taking but on its possible connections to students' plans to major in a STEM field in college. Though the apparent beneficial relationships of early conversations do not seem to extend to such plans, any unforced increases to the number of students taking advanced math courses in high school may lead to improvements in the pipeline to earning STEM degrees. That is, the strong and significant associations detected in this study between advanced math course taking and planning to major in a STEM field suggest the possibility that earlier student-parent conversations might have some influence to the extent that they affect course taking decisions. As stressed at many points before, however, identifying these causal pathways remains beyond the scope of this study.

Conclusion

In this dissertation I set out to investigate whether early student and parent conversations concerning what to do after high school were associated with three important outcomes in the STEM pipeline: taking advanced math courses in high school, taking extra science courses in high school, and expressing plans to major in a STEM field of study in college. I also sought evidence related to whether statistical models predicting these outcomes varied, as theory suggests, by gender. In general, I find support for the notion that, net of other theoretically relevant predictors, beginning student and parent conversations prior to the eighth grade is positively associated with whether a student took advanced math courses in high school. Relationships between the timing of conversations and the other outcomes of interest in this study were found to be statistically non-significant when controlling for other factors in the models.

Based on the contextual and theoretical frameworks that guide this study, it is unsurprising that being an early converser was significantly associated with taking advanced math courses in the final aggregate models, even after controlling for all other factors. As Adelman (2006) and many other others have noted, early work in mathematics prepares students for the more advanced work required in later courses and years. Students who begin more challenging work at the earliest points of their academic careers, then, should be even more equipped to take the most advanced courses in high school. The findings in this study support the notion that students may be aided in this process by beginning discussions with parents concerning what to do after high school prior to the eighth grade. Though to some, this may seem too early a time to have such discussions with children, foundational algebra courses for students are more frequently being offered to students in the middle school years. Thus, preparing them for their course trajectories in the seventh grade and before is completely logical.

This study does have a few limitations that bear mentioning. First, the data from the NHHSSS relate to a small and homogenous state. Thus, the findings cannot be extrapolated to the larger and more diverse population of the United States. Second, the methodological approach taken in the study lacks the criteria necessary to identify causal relationships between the predictors and outcomes of interest.

Finally, the NHHSSS was not designed with the intention of measuring factors and outcomes specifically related to the STEM pipeline. As such, the construction of some of the variables employed in this study are subject to a degree of scrutiny.

Despite these limitations, this dissertation represents an important contribution to the literature on the STEM pipeline. It extends the methodological rigor of studies related to students' early educational experiences and their eventual course taking in high school (*e.g.*, Simpkins et al., 2006), and expands the analysis to a much larger sample size using data that is some two decades more current than prior research. It also takes advantage of a distinct dataset from New Hampshire that captures factors of interest, such as the timing of students' and parents' earliest conversations about what to do after high school, that no other large data sets are known to include. This applies even to large nationally-representative datasets such as NELS, ELS, and even the most recently concluded HSLS:09. Though I cannot answer conclusively from this study whether earlier information about what to do after high school leads more students to take advanced math courses or extra science courses in high school or to make plans to major in a STEM field in college, it does establish a foundation for further investigation along these lines. Findings from this study also lend support to the notion that males and females may have experiences in the STEM pipeline that vary considerably. When possible, researchers should undertake efforts to account for this heterogeneity in some way.

Future studies concerning this topic should be designed to follow students beginning in elementary school and extending into postsecondary education and beyond. To my knowledge, no such study currently exists, nor are national datasets equipped to address such questions. This represents an unfortunate gap in the development of our knowledge of important areas of the STEM pipeline. What is worse, though this topic is one of immediate educational and economic importance, obtaining the type of data needed to answer these questions fully would require enough years to follow students from their childhood into the labor force. Because of this, it may be that conclusive answers to the questions posed in this study will remain undiscovered. On the other hand, state education agencies collect and analyze increasingly robust datasets relative to students in their own state. A number of studies have linked these data to economic and workforce indicators drawn from other governmental organizations. It is possible that a retrospective survey similar to the NHHSSS administered in a more diverse state and at an even earlier date might prove quite valuable in further investigating the research questions in this study. While any results would also not reflect the larger national population, repeating the study across multiple states could alleviate some of the related concerns.

Future studies should also leverage questions that are crafted to address students' early experiences receiving information and having conversations about STEM-specific topics. Though useful, the predictor variable of interest in this study can only be safely considered to relate to general conversations about what to do after high school. While any number of these conversations could have centered around STEM education and careers, this is not something that can be determined. Questions about STEM pipeline factors should also ask about the source of information. It may prove instructive to analyze whether students with different levels of economic, cultural, and social capitals might benefit in varying ways from conversations with individuals other than their parents, such as teachers, school counselors, friends, other family members, and mentors.

Regardless of whether we learn conclusive answers to the research questions in this study in the immediate future, the findings from this study present evidence that at least parents may have good reason to begin discussions with their students about what to do after high school well before students reach the middle school years. School personnel should also be trained and instructed to have these conversations with students in order to reinforce what some hear at home and to introduce the information to others with lower levels of social and cultural capitals. Such interventions require little investment from stakeholders and have the potential to lead to important gains in STEM pipeline outcomes, and may even, as some groups such as the Algebra Project suggest, improve equity and strengthen the democratic functions of our P-20 education systems.

REFERENCES

Achieve. (2008). *The building blocks of success: Higher level math for all students*. Retrieved from http://www.achieve.org/files/BuildingBlocksofSuccess.pdf

ACT. (2016). *The condition of STEM 2016: New Hampshire*. Retrieved from http://www.act.org/stemcondition

Adelman, C. (2006). *The toolbox revisited*. *Paths to degree completion from high school through college*. U.S. Department of Education. Washington, D.C.: Office of Vocational and Adult Education.

Altonji, J. (1995). The effects of high school curriculum on education and labor market outcomes. *The Journal of Human Resources*, *30*(3), 409-438.

Ardies, J., De Maeyer, S., & Gijbels, D. (2015). A longitudinal study on boys' and girls' career aspirations and interest in technology. *Research in Science & Technological Education*, *33*(3), 366-386.

Atanda, R. (1999). Do gatekeeper courses expand education options? *Education Statistics Quarterly, 1*(1), 33-38.

Bahrick, H., Hall, L., & Berger, S. (1996) Accuracy and distortion in memory for high school grades. *Psychological Sciences*, *7*(5), 265-271.

Baker, D., & Leary, R. (1995). Letting girls speak out about science. *Journal of Research in Science Teaching*, *32*(1), 3-27.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, New Jersey: Prentice-Hall.

Barton, A., Tan, E., & Rivet, A. (2008). Creating hybrid spaces for engaging school science among urban middle school girls. *American Education Research Journal*, *45*(1), 68-103.

Becker, G. (1965). A theory of the allocation of time. *The Economic Journal*, *75*(299), 493-517.

Becker, G. (1993). *Human capital: A theoretical and empirical analysis, with special reference to education* (3rd ed.). Chicago: The University of Chicago Press.

Bell, A. D., Rowan-Kenyon, H.T., & Perna, L. (2009). College knowledge of 9th and 11th grade students. *The Journal of Higher Education*, *80*, 663-685.

Bell, J. (2001). Investigating gender differences in the science performance of 16-year-old pupils in the UK. *International Journal of Science Education*, *23*(5), 469-486.

Blickenstaff, J. (2005). Women and science careers: Leaky pipeline or gender filter? *Gender and Education*, *17*(4), 369-386.

Blustein, D., Barnett, M., Mark, S., Depot, M., Lovering, M., Lee, Y., … DeBay, D. (2013). Examining urban students' constructions of a STEM/career development intervention over time. *Journal of Career Development*, *40*(1), 40-67.

Bonous-Hammarth, M. (2000). Pathways to success: Affirming opportunities for science, mathematics, and engineering majors. *Journal of Negro Education*, *69*(1/2), 92-11.

Bonous-Hammarth, M., & Allen, W. (2005). A dream deferred: The critical factor of timing in college preparation and outreach. In W.G. Tierney, Z.B. Corwin, & J.E. Colyar (Eds.), *Preparing for college: Nine elements of effective outreach* (pp.155-171). Albany, SUNY Press.

Bourdieu, P. (1977). Cultural reproduction and social reproduction. In J. Karabel & A.H. Halsey (Eds.), *Power and ideology in education* (pp. 487-511). New York: Oxford.

Bourdieu, P. (1986). The forms of capital. In J.G. Richardson (Ed.), *Handbook of theory and research for the sociology of education* (pp. 241-285). New York: Greenwood.

Bowen, W., Chingos, M., & McPherson, M. (2009). *Crossing the finish line: Completing college at America's public universities*. Princeton, NJ: Princeton University Press.

Bozick, R., & Ingels, S.J. (2007). *Mathematics coursetaking and achievement at the end of high school: Evidence from the Education Longitudinal Study of 2002 (ELS:2002)* (NCES 2008-319). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC.

Bozick, R. & Lauff, E. (2007). *Educational Longitudinal Study of 2002 (ELS:2002): A first look at the initial postsecondary experiences of the high school sophomore class of 2002* (NCES 2008-308). U.S. Department of Education. Washington D.C.: National Center for Education Statistics.

Byun, S., Irvin, M., & Bell, B. (2015). Advanced math course taking: Effects on math achievement and college enrollment. *The Journal of Experimental Education*, *83*(4), 439-468.

Cameron, S., & Heckman, J. (2001). The dynamics of educational attainment for Black, Hispanic, and white males. *Journal of Political Economy*, *109*, 455-499.

Carter, D. (1999). The impact of institutional choice and environments on African-American and white students' degree expctations. *Research in Higher Education , 40*, 1999.

Ceci, S., Williams, W., & Barnett, S. (2009). Women's underrepresentation in science: Sociocultural and biological considerations. *Psychological Bulletin*, *135*(2), 218-261.

Chen, X. (2013). STEM attrition: College students' paths into and out of STEM fields (NCES 2014-001). National Center for Education Statistics, Institute of Education Sciences. Washington, D.C.: U.S. Department of Education.

Christensen, R., Knezek, G., & Tyler-Wood, T. (2014). Student perceptions of science, technology, engineering, and mathematics (STEM) content and careers. *Computers in Human Behavior*, *34*, 173-186.

Cleaves, A. (2005). The formation of science choices in secondary school. *International Journal of Science Education*, *27*(4), 471-486.

Clotfelter, C., Ladd, H., & Vigdor, J. (2013). Algebra for 8th graders: Evidence on its effects from 10 North Carolina districts (Working Paper No. w18649). Retrieved from National Bureau of Economic Research website: www.nber.org/papers/w18649.pdf

Clotfelter, C., Ladd, H., & Vigdor, J. (2015). The aftermath of accelerating Algebra: Evidence from district policy initiatives. *The Journal of Human Resources*, *50*(1), 159-188.

Coleman, J. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, *94*, S95-S120.

Committee on Prospering in the Global Economy of the 21st-Century. (2007). *Rising above the gathering storm: Energizing and employing America for a brighter economic future.* Washington, D.C.: The National Academies Press.

Corbett, C., Hill, C., St. Rose, A. (2008). *Where the girls are: The facts about gender equity in education.* American Association of University Women. Washington, D.C.: AAUW Educational Foundation.

Cordova-Wentling, R., & Camacho, C. (2006). *Women engineers: Factors and obstacles related to the pursuit of a degree in engineering*. Paper presented at the American Society of Engineering Education, Chicago, IL.

Dell, E., Christman, J., & Garrick, R. (2011). Assessment of an engineering technology outreach program for 4th-7th grade girls. *American Journal of Engineering Education*, *2*(1), 19-34.

Demaris, A. (2004). *Regression with social data: Modeling continuous and limited response variables* (Vol. 417). Hoboken, New Jersey: Wiley-Blackwell.

Domina, T., McEachin, A., Penner, A, & Penner, E. (2015). Aiming high and falling short: California's eighth-grade algebra-for-all effort. *Education Evaluation and Policy Analysis*, *37*, 275-295.

Dozier, R., Blaisdell, S., & Anderson-Rowland, M. (1997). Teaching and learning in an era of equality: An engineering program for middle school girls. *Proceedings of the 1997 27th annual conference on Frontiers in Education,* 512-514. Pittsburg, PA.

Eccles, J. (1987). Gender roles and women's achievement-related decisions. *Psychology of Women Quarterly*, *11*, 135-172.

Eccles, J., Vida, M., & Barber, B. (2004). The relation of early adolescents' college plans and both academic ability and task-value beliefs to subsequent college enrollment. *Journal of Early Adolescence*, *24*(1), 63-77.

Engberg, M., & Wolniak, G. (2009). Navigating disparate pathways to college: Examining the conditional effects of race on enrollment decisions. *Teachers College Record*, *111*, 2255- 2279.

Flint, T. A. (1993). Early awareness of college financial aid: Does it expand choice? *Review of Higher Education*, *16*, 309–327.

Freeman, K. (1997). Increasing African American participation in higher education: African American students' high school perspectives. *Journal of Higher Education*, *68*, 523-550.

Gaertner, M., Kim, J., DesJardins, S., & McClarty, K. (2014). Preparing students for college and careers: The causal role of Algebra II. *Research in Higher Education*, *55*, 143-165.

Gamoran, A. & Hannigan, E. (2000). Algebra for everyone? Benefits of college preparatory mathematics for students with diverse abilities in early secondary school. *Educational Evaluation and Policy Analysis, 22*(3)*,* 241-254.

Gardner, D.P. (1983). *A nation at risk*. Washington, D.C. The National Commission on Excellence in Education, U.S. Department of Education.

George-Jackson, C., & Gast, M.J. (2015). Addressing information gaps: Disparities in financial awareness and preparedness on the road to college. *Journal of Student Financial Aid*, *44*, 202-234.

Gonzales, P., Guzmán, J., Partelow, L., Pahlke, E., Leslie, J., Kastberg, D., & Williams, T. (2004). *Highlights from the Trends in International Mathematics and Science Study (TIMSS) 2003* (NCES 2005-005). U.S. Department of Education, National Center for Education Statistics. Washington, D.C.: US Government Printing Office.

Hamrick, F., & Stage, F. (1998). High minority enrollment, high school-lunch rates: Predisposition to college. *The Review of Higher Education*, *21*, 343-357.

Harding, J., Parker, M., & Toutkoushian, R. (2017). Deciding about college: How soon is soon enough? *Teachers College Record.*

Hazari, Z., Tai, R., & Sadler, P. (2007). Gender differences in introductory university physics performance: The influence of high school physics preparation and affective factors. *Science Education*, *91*, 847-876.

Hill, C., Corbett, C., & St. Rose, A. (2010). *Why so few? Women in science, technology, engineering and mathematics.* American Association of University Women. Washington, D.C.: AAUW Educational Foundation.

Hossler, D., & Gallagher, K. (1987). Studying student college choice: A three-phase model and the implications for policymakers. *College and University*, *62*(3), 207-221.

Hsin, A., & Xie, Y. (2014). Explaining Asian Americans' academic advantage over whites. *Proceedings of the National Academy of Sciences*, *111*(23), 8416-8421.

Hurtado, S., Inkelas, K., Briggs, C., & Rhee, B. (1997). Differences in college access and choice among racial/ethnic groups: Identifying continuing barriers. *Research in Higher Education*, *38*, 43-75.

Joensen, J., & Nielsel, H. (2009). Is there a causal effect of high school math on labor market outcomes? *The Journal of Human Resources*, *44*(1), 171-198.

Jones, G., Howe, A, & Rua, M. (2000). Gender differences in students' experiences, interests, and attitudes toward science and scientists. *Science Education*, *84*(2), 180-192.

Kao, G., & Tienda, M. (1998). Educational aspirations of minority youth. *American Journal of Education*, *106*, 349-384.

King, J. (1996). *The decision to go to college: Attitudes and experiences associated with college attendance among low-income students.* Washington, D.C.: The College Board.

Kuenzi, J. (2008). Science, Technology, Engineering, and Mathematics (STEM) Education: Background, policy, and legislative action. *Congressional Research Service Reports*. Paper 35. Washington, D.C. Congressional Research Service.

Kuncel, N., Credé, M., Thomas, L. (2005). The validity of self-reported grade point averages, class ranks, and test scores: A meta-analysis and review of the literature. *Review of Educational Research*, *75*(1), 63-82.

Lemke, J. (2001). Articulating communities: Sociocultural perspectives on science education. *Journal of Research in Science Teaching*, *38*(3), 296-316.

Lent, R., Brown, S., & Hackett, G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice, and performance. *Journal of Vocational Behavior*, *45*, 79-122.

Lent, R., Brown, S., & Hackett, G. (2000). Contextual supports and barriers to career choice: A social cognitive analysis. *Journal of Counseling Psychology*, *47*, 36-49.

Leslie, L., McClure, G., & Oaxaca, R. (1998). Women and minorities in science and engineering. *The Journal of Higher Education*, *69*(3), 239-276.

Long, M., Conger, D., & Iatarola, P. (2012). Effects of high school course-taking on secondary and postsecondary success. *American Educational Research Journal*, *49*(2), 285-322.

Long, J., & Freese, J. (2014). *Regression models for categorical dependent variables using Stata* (3rd ed.). College Station, TX: Stata Press.

Loveless, T. (2008). The misplaced math student: Lost in eighth-grade algebra. Special release of the *2008 Brown Center Report on American Education. How well are American Students Learning.* Retrieved from https://www.brookings.edu/wp-content/uploads/ 2016/06/0922_education_loveless.pdf

Loveless, T. (2013). *The algebra imperative: Assessing algebra in a national and international context*. Brown Center on Education Policy at Brookings. Retrieved from https://www.brookings.edu/research/the-algebra-imperative-assessing-algebra-in-a-national-and-international-context/

Madigan, T. (1997). *Science proficiency and course taking in high school. The relationship of science course-taking patterns to increases in science proficiency between 8th and 12th grades* (NCES-97-838). U.S. Department of Education. National Center for Education Statistics. Washington, D.C.

Maltese, A., & Tai, R. (2010). Eyeballs in the fridge: Sources of early interest in science. *International Journal of Science Education*, *32*(5), 669-685.

Maltese, A., & Tai, R. (2011). Pipeline persistence: Examining the association of educational experiences with earned degrees in STEM among U.S. students. *Science Education*, *95*(5), 877-907.

Maple, S. & Stage, F. (1991). Influences on the choice of math/science major by gender and ethnicity. *American Educational Research Journal*, *28*(1), 37-60.

Mau, W., & Bikos, L. (2000). Educational and vocational aspirations of minority and female students: A longitudinal study. *Journal of Counseling and Development*, *78*, 186-194.

Mincer, J. (1958). Investment in human capital and personal income distribution. *Journal of Political Economy*, *66*(4), 281-302.

Moses, R., & Cobb, C. (2002). *Radical equations: Civil rights from Mississippi to the Algebra Project*. Boston: Beacon Press.

Museus, S., Palmer, R., Davis, R., & Maramba, D. (2011). Special issue: Racial and ethnic minority students' success in STEM education. *ASHE Higher Education Report*, *36*(6), 1-140.

Navarro, R., Flores, L., & Worthington, R. (2007). Mexican American middle school students' goal intentions in mathematics and science: A test of Social Cognitive Career Theory. *Journal of Counseling Psychology*, *54*(3), 320-335.

National Girls Collaborative Project. (2016). *Statistics: State of Girls and Women in STEM.* Retrieved from https://ngcproject.org/statistics

National Science Board. (2016). *Science and engineering indicators 2016* (NSB-2016-1). Arlington Virginia: National Science Foundation.

National Science Foundation. (2015). *Women, minorities, and persons with disabilities in science and engineering* (NSF 15-311). National Center for Science and Engineering Statistics. Arlington, VA.

New Hampshire Department of Education. (2008). State totals- Enrollments by grade as of October, 1 2007. Retrieved from https://www.education.nh.gov/data/documents/ fall_enroll07_08.pdf

New Hampshire Department of Education. (2009). State totals- Enrollments by grade as of October, 1 2008. Retrieved from https://www.education.nh.gov/data/ documents/fall_enroll08_09.pdf

New Hampshire Department of Education. (2010). State totals- Enrollments by grade as of October, 1 2009. Retrieved from https://www.education.nh.gov/data/ documents/fall_enroll09_10.pdf

New Hampshire Department of Education. (2015). State totals- Ten years public and private fall enrollments 2005-2006 through 2014-2015. Retrieved from https://www.education.nh.gov/data/ documents/ten_year2005.pdf

New Hampshire Partnership for the Advancement of Postsecondary Education Research. (2002). *Measuring aspirations and participation: New Hampshire High School Senior Survey*. Retrieved from https://www.education.nh.gov/career/guidance/documents/ srsurvey2002.pdf

---. (2007) *Measuring aspirations and participation: New Hampshire High School Senior Survey*. https://www.education.nh.gov/career/guidance/documents/srsurvey2007.pdf

Nicholls, G., Wolfe, H., Besterfield-Sacre, M., & Shuman, L. (2010). Predicting STEM degree outcomes based on eighth grade data and standardized test scores. *Journal of Engineering Education*, *99*(3), 209-223.

Nicholls, G., Wolfe, H., Besterfield-Sacre, M., Shuman, L., & Larpkiattaworn, S. (2007). A method for identifying variables for predicting STEM enrollment. *Journal of Engineering Education*, *96*(1) , 33-44.

Nomi, T. (2012). The unintended consequences of an algebra-for-all policy on high-skill students: Effects of instructional organization and students' academic outcomes. *Educational Evaluation and Policy Analysis*, *34*, 489-505.

Nord, C., Roey, S., Perkins, R. Lyons, M. Lemanski, N., Tamir, Y.,…, Schuknect, J. (2011). America's high school graduates: Results from the 2009 NAEP High School Transcript Study (NCS 2011-462). U.S. Department of Education. National Center for Education Statistics. Washington, D.C.

Oakes, J. (1990). *Lost talent: The underparticipation of women, minorities, and disabled persons in science*. National Science Foundation. Santa Monica, CA: Rand.

Olson, S., & Riordan, D.G. (2012). Engage to excel: Producing one million college graduates with degrees in science, technology, engineering, and math. Report to the President. *Executive Office of the President*.

Organisation for Economic Co-operation and Development (OECD). 2012. International Migration Outlook 2012. Paris: OECD.

Orr, A. (2003). Black-white differences in Achievement: The importance of wealth. *Sociology of Education*, *76*, 281-304.

Osborne, J., Simon, S., & Collins, S. (2003). Attitudes toward science: A review of the literature and its implications. *International Journal of Science Education*, *25*(9), 1049-1079.

Perna, L. (2000). Differences in the decision to attend college among African Americans, Hispanics, and Whites. *The Journal of Higher Education*, *71*(2), 117-141.

Perna, L., & Steele, P. (2011). The role of context in understanding the contributions of financial aid to college opportunity. *Teachers College Record*, *113*, 895-933.

Perna, L., & Titus, M. (2005). The relationship between parental involvement as social capital and college enrollment: An examination of racial group differences. *The Journal of Higher Education*, *76*, 485-518.

Plank, S., & Jordan, W. (2001). Effects of information, guidance, and actions on postsecondary destinations: A study of talent loss. *American Education Research Journal*, *38*, 947–979.

Riegle-Crumb, C., & Moore, C. (2013). Examining gender inequality in a high school Engineering Course. *American Journal of Engineering Education*, *4*(1), 55-66.

Rose, H., & Betts, J. (2004). The effect of high school courses on earnings. *The Review of Economics and Statistics*, *86*, 497-513.

Sadker, M., Sadker, D., & Klein, S. (1993). The issue of gender in elementary and secondary schools. In G. Grant (Ed.), *Review of Research in Education 17* (pp. 269-334). Washington, DC: American Educational Research Association.

Schneider, B., Kirst, M., & Hess, F. (2003). Strategies for success: High School and Beyond. *Brookings Papers on Educational Policy*, *2003*(6), 55-93.

Schneider, B., Swanson, C., & Riegle-Crumb, C. (1998). Opportunities for learning: Course sequence and positional advantage. *Social Psychology of Education*, *2*, 25-53.

Simpkins, S., Davis-Kean, P., & Eccles, J. (2006). Math and science motivation: A longitudinal examination of the links between choices and beliefs. *Developmental Psychology*, *42*(1), 70-83.

Somers, P., Cofer, J., & VanderPutten, J. (2002). The early bird goes to college: The link between early college aspirations and postsecondary matriculation. *Journal of College Student Development*, *43*, 93-107.

Stanton-Salazar, R., & Dornbusch, S. (1995). Social capital and the reproduction of inequality: Information networks among Mexican-origin high school students. *Sociology of Education*, *68*, 93-107.

St. John, E. (1991). What really influences minority attendance? Sequential analyses of the High School and Beyond Sophomore Cohort. *Research in Higher Education*, *32*, 141-158.

Tai, R., Liu, C., Maltese, A., & Fan, X. (2006). Planning early for careers in science. *Science*. *312*, 1143-1144.

Tai, R., Sadler, P., & Loehr, J. (2005). Factors influencing success in introductory college chemistry. *Journal of Research in Science Teaching*, *42*(9), 987-1012.

The Algebra Project. (2016). *Who we are*. Retrieved from http://www.algebra.org/whoweare.php

Toutkoushian, R., & Paulsen, M. (2016). *Economics of higher education: Background, concepts, and applications*. The Netherlands: Springer.

Tracy, L. (2006) Required subjects and credits for high school graduation (Algebra credit). Technical Advisory #6. New Hampshire Department of Education. Retrieved from http://education.nh.gov/standards/documents/advisory6.pdf

Trusty, J. (2002). Effects of high school course-taking and other variables on choice of science and mathematics college majors. *Journal of Counseling and Development, 80*(4), 464-474.

Tyson, W., Lee, R., Borman, K., & Hanson, M. (2007). Science, technology, engineering, and mathematics (STEM) pathways: High school science and math coursework and postsecondary degree attainment. *Journal of Education for Students Placed at Risk*, *12*(3), 243-270.

United States Department of Education. (1997). *Mathematics equals opportunity*. White paper prepared for U.S. Secretary of Education Richard W. Riley. Washington, D.C.: U.S. Department of Education.

United States Immigration and U.S. Customs Enforcement. (2016). *STEM Designated Degree Program List Effective May 10, 2016*. Retrieved from https://www.ice.gov/sites/default/ files/documents/Document/2016/stem-list.pdf

Ware, N., & Lee, V. (1988). Sex differences in choice of college science majors. *American Education Research Journal*, *25*(4), 593-614.

Webber, K., & González Canché, M. (2015). Not equal for all: Gender and race differences in salary for doctoral degree recipients. *Research in Higher Education*, *56*(7), 645-672.

Wilgoren, J. (2001, January 7). Algebra Project: Bob Moses empowers students. *The New York Times*. Retrieved from http://www.nytimes.com/2001/01/07/education/algebra-project-bob-moses-empowers-students.html?pagewanted=all

Xie, Y., & Schauman, K. (2003). *Women in science: Career processes and outcomes.* Cambridge, MA: Harvard University Press.

Zhang, L., & Barnett, M. (2015). How high school students envision their STEM career pathways. *Cultural Studies of Science Education*, *10*, 637-656.

APPENDICES

APPENDIX A

Measuring Aspirations and Participation: New Hampshire Senior Survey

Spring 2007

STUDENT IDENTIFICATION PLEASE COMPLETE THE INFORMATION BELOW.

Name ____
(First Name) (Middle Initial) (Last Name)

Mailing Address ____________________ **State & Zip Code** ____________________

City/Town ____

Birth Date ____________ **Phone Number** ____________________

Student Indentifier ____________________ **High School** ____________________
(optional)

INSTRUCTIONS

After reading each question, fill in the circle for the option that best describes your answer.

MARKING INSTRUCTIONS
USE NO. 2 PENCIL ONLY
CORRECT MARK INCORRECT MARKS

Section A TO BE ANSWERED BY ALL STUDENTS

GENERAL INFORMATION

1. **In which New Hampshire county do you currently live?**
- ○ Belknap (1)
- ○ Carroll (2)
- ○ Cheshire (3)
- ○ Coos (4)
- ○ Grafton (5)
- ○ Hillsborough (6)
- ○ Merrimack (7)
- ○ Rockingham (8)
- ○ Strafford (9)
- ○ Sullivan (10)
- ○ Out-of-state (11)

2. **Are you:**
- ○ Male (1)
- ○ Female (2)

3. **Ethnicity:**
- ○ Hispanic or Latino (1)
- ○ Not Hispanic or Latino (2)

4. **Race:**
(Please mark all that apply.)
- ○ White (1)
- ○ Black or African-American (2)
- ○ American Indian or Alaska Native (3)
- ○ Asian (4)
- ○ Native Hawaiian or Other Pacific Islander (5)

YOUR FAMILY

5. **What is your best estimate of the total income that people in your household earned in 2006 from ALL sources?**
- ○ Less than $25,000 (1)
- ○ $25,000 but less than $50,000 (2)
- ○ $50,000 but less than $75,000 (3)
- ○ $75,000 but less than $100,000 (4)
- ○ $100,000 or more (5)
- ○ Don't know (6)

6. **With whom do you live?**
- ○ Your mother & father (1)
- ○ Your mother & stepfather (2)
- ○ Your father & stepmother (3)
- ○ Alternate between mother and father (4)
- ○ Mother only (5)
- ○ Father only (6)
- ○ Your grandparents, aunts, uncles, or other relatives (7)
- ○ Some other adults (i.e., guardians, foster parents, etc.) (8)
- ○ On my own or with friends (9)

7. **What is the highest level of education completed by each of your parents?**

	Mother	Father
Eighth grade or less (1)	○	○
Some high school (2)	○	○
High school diploma (3)	○	○
Certificate from business or technical school of less than two years (4)	○	○
Some college (5)	○	○
Associate's Degree—2 years (6)	○	○
Bachelor's Degree—4 years (7)	○	○
Some graduate or professional school (8)	○	○
Graduate or professional degree (9)	○	○

1234567890

PLEASE DO NOT WRITE IN THIS AREA

8. What is the current occupation status of your parents?

	Mother	Father
Employed full time (1)	◯	◯
Employed part time (2)	◯	◯
A full-time homemaker (3)	◯	◯
Unemployed (4)	◯	◯
Retired (5)	◯	◯
Not working due to disability (6)	◯	◯
Deceased (7)	◯	◯
Other (8)	◯	◯

ACADEMIC EXPERIENCE

9. Please fill in the circle indicating the number of years you have studied (for high school credit) each of the subject areas listed below. Please include this year. If you have taken full years of a subject plus a half year, round up to the higher number of years.

	Number of Years
A. English	⓪①②③④⑤
B. Foreign Languages	⓪①②③④⑤
C. Algebra I/Geometry	⓪①②③④⑤
D. Algebra II/Trigonometry/ Pre-Calculus/Calculus/Statistics	⓪①②③④⑤
E. Other General Math	⓪①②③④⑤
F. Sciences	⓪①②③④⑤
G. Social Studies and History	⓪①②③④⑤
H. Art, Drama, Music, and Dance	⓪①②③④⑤
I. Vocational and Technical Education	⓪①②③④⑤
J. Business Studies	⓪①②③④⑤
K. Computer Studies	⓪①②③④⑤
L. Physical Education/Health	⓪①②③④⑤

10. Please fill in the circle indicating your average grade in high school for the courses you have taken.

	Grade
A. English	Ⓐ Ⓑ Ⓒ Ⓓ Ⓕ
B. Foreign Languages	Ⓐ Ⓑ Ⓒ Ⓓ Ⓕ
C. Mathematics (all mathematics classes)	Ⓐ Ⓑ Ⓒ Ⓓ Ⓕ
D. Sciences	Ⓐ Ⓑ Ⓒ Ⓓ Ⓕ
E. Social Studies and History	Ⓐ Ⓑ Ⓒ Ⓓ Ⓕ
F. Art, Drama, Music, and Dance	Ⓐ Ⓑ Ⓒ Ⓓ Ⓕ
G. Vocational and Technical Education	Ⓐ Ⓑ Ⓒ Ⓓ Ⓕ
H. Business Studies	Ⓐ Ⓑ Ⓒ Ⓓ Ⓕ
I. Computer Studies	Ⓐ Ⓑ Ⓒ Ⓓ Ⓕ
J. Physical Education/Health	Ⓐ Ⓑ Ⓒ Ⓓ Ⓕ

11. Please indicate the range where your cumulative grade point average falls.

- ◯ 3.75 or higher (1)
- ◯ 3.50–3.74 (2)
- ◯ 3.25–3.49 (3)
- ◯ 3.00–3.24 (4)
- ◯ 2.50–2.99 (5)
- ◯ 2.00–2.49 (6)
- ◯ 1.50–1.99 (7)
- ◯ 1.00–1.49 (8)
- ◯ Lower than 1.00 (9)

12. Which of the following work-based or community service learning experiences did you participate in *for high school credit*?
(Please mark all that apply.)

- ◯ Job shadowing (1)
- ◯ Mentorship (2)
- ◯ Apprenticeship (3)
- ◯ Work study (4)
- ◯ Cooperative education (5)
- ◯ Internship/Practicum (6)
- ◯ Community service/ volunteer work (7)
- ◯ I did not participate in any programs (8)

13. How helpful has your work-based or community service learning experience been in helping you formulate your future career plans?

- ◯ Very helpful (1)
- ◯ Somewhat helpful (2)
- ◯ Not helpful (3)

HIGH SCHOOL EXPERIENCE

14. Please rate the quality of instruction provided by your high school in the following areas.

	Excellent	Satisfactory	Unsatisfactory	Wasn't Taught
Communication				
A. Express myself so that others can understand me	◯	◯	◯	◯
B. Listen so that I can understand others	◯	◯	◯	◯
C. Read a variety of materials with understanding	◯	◯	◯	◯
D. Write for a variety of purposes	◯	◯	◯	◯
E. Use computers and other technology to conduct research, gather information, and communicate	◯	◯	◯	◯
Reasoning and Problem Solving				
F. Ask meaningful questions	◯	◯	◯	◯
G. Solve difficult problems	◯	◯	◯	◯
H. Think abstractly and creatively	◯	◯	◯	◯
I. Approach problem solving with an open mind, healthy skepticism, and persistence	◯	◯	◯	◯
Personal Development				
J. Set personal goals and act on them	◯	◯	◯	◯
K. Develop productive and satisfying relationships with others	◯	◯	◯	◯
L. Be a productive worker	◯	◯	◯	◯
M. Maintain a healthy way of life	◯	◯	◯	◯
N. Know my unique worth and personal competence	◯	◯	◯	◯
O. Make informed decisions	◯	◯	◯	◯
Civic and Social Responsibility				
P. Practice the duties and responsibilities of citizenship	◯	◯	◯	◯
Q. Deal with different kinds of people	◯	◯	◯	◯
R. Deal with change in my home, school, community, and workplace	◯	◯	◯	◯
Science, Math, and Technology				
S. Understand and apply mathematics in everyday life	◯	◯	◯	◯
T. Understand and apply science in everyday life	◯	◯	◯	◯
U. Understand and apply technology in everyday life	◯	◯	◯	◯

Question #14 continued

	Excellent	Satisfactory	Unsatisfactory	Wasn't Taught
Arts, Language, and Literature				
V. Use music, art, dance, and literature to enhance everyday life	○	○	○	○
W. Understand and use the conventions (grammar, usage) and structures (sentence, paragraph) of the English language	○	○	○	○
X. Use a non-native language to read, write, listen, and speak	○	○	○	○
History and Social Sciences				
Y. Understand how societies and their systems work	○	○	○	○
Z. Differentiate among fact, opinion, and interpretation	○	○	○	○
AA. Understand and apply NH, United States, and world history in everyday life	○	○	○	○
BB. Understand and apply geography in everyday life	○	○	○	○
CC. Understand and apply economics in everyday life	○	○	○	○

If an answer does not apply, leave blank.

15. Please rate how much you agree with each of the following statements.

	Strongly Agree	Agree	Disagree	Strongly Disagree
A. My school has provided me with a good education.	○	○	○	○
B. My school has provided me with the guidance I need to reach my goals.	○	○	○	○
C. My school has provided a safe environment for learning.	○	○	○	○
D. My teachers have challenged me to do my best work.	○	○	○	○
E. My teachers have given me a reasonable amount of work to do.	○	○	○	○
F. My teachers had a positive influence on me.	○	○	○	○
G. My guidance counselor had a positive influence on me.	○	○	○	○
H. My coaches had a positive influence on me.	○	○	○	○
I. My principal and other school administrators had a positive influence on me.	○	○	○	○
J. My classes have usually been interesting.	○	○	○	○
K. My classes have usually been taught in ways I could understand.	○	○	○	○
L. I have been taught how the things I learn apply to real life.	○	○	○	○
M. I have been taught how to be a good group or team member.	○	○	○	○
N. School rules have been fair.	○	○	○	○
O. School rules have been enforced consistently and fairly.	○	○	○	○

16. How many hours a week do you spend studying?

- ○ None (1)
- ○ 1–5 hours (2)
- ○ 6–10 hours (3)
- ○ 11–15 hours (4)
- ○ 16–20 hours (5)
- ○ More than 20 hours (6)

17. How many hours do you use a computer for school-related activities?

- ○ None (1)
- ○ 1–5 hours (2)
- ○ 6–10 hours (3)
- ○ 11–15 hours (4)
- ○ 16–20 hours (5)
- ○ More than 20 hours (6)

18. While in high school, I earned college credit through the following programs:
(Please mark all that apply.)

	Participated	Earned College Credit
A. Project Running Start (1)	○	○
B. Advanced Placement (class) (2)	○	○
C. Advanced Placement (via distance education) (3)	○	○
D. Project Lead the Way (4)	○	○
E. The Future Educators Academy (5)	○	○
F. National Academy of Finance (6)	○	○
G. Enrolled in a college course offered at a college (7)	○	○
H. Enrolled in a college course via the Internet (8)	○	○
I. Did not participate (9)	○	○
J. Did not earn college credit (10)	○	○

EXTRACURRICULAR EXPERIENCE

19. Which of the following extra- or co-curricular activities have you participated in during high school?
(Please mark all that apply.)

- ○ Athletics (school- and non-school related) (1)
- ○ Student government (2)
- ○ Band/chorus/orchestra (3)
- ○ Honor societies (4)
- ○ Theater/drama/dance (5)
- ○ Other school clubs and committees (e.g., school newspaper, yearbook, Math League) (6)
- ○ Non-school clubs (e.g., Scouts) (7)
- ○ ROTC (8)
- ○ Church groups/activities (9)
- ○ Volunteer work (10)
- ○ Hobbies (11)

20. How many hours a week during your senior year did you spend doing extra- or co-curricular activities?

- ○ None (1)
- ○ 1–5 hours (2)
- ○ 6–10 hours (3)
- ○ 11–15 (4)
- ○ 16–20 hours (5)
- ○ More than 20 hours (6)

WORK EXPERIENCE

21. Which of the following work activities have you participated in during high school?
(Please mark all that apply.)

- ○ Paid job (1)
- ○ Volunteer work (2)

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22. What impact have your work-related activities had on your school performance?

- ◯ Enhanced school performance (1)
- ◯ Interfered with school performance (2)
- ◯ Had no effect on school performance (3)
- ◯ Did not work or participate in work-related activities (4)

23. During your senior year, how many hours a week on average did you work?

Paid	Volunteer
◯ None (1)	◯ None (1)
◯ 1–10 hours (2)	◯ 1–10 hours (2)
◯ 11–20 hours (3)	◯ 11–20 hours (3)
◯ 21–30 hours (4)	◯ 21–30 hours (4)
◯ 31–40 hours (5)	◯ 31–40 hours (5)
◯ 41+ hours (6)	◯ 41+ hours (6)

INFORMATION ABOUT CAREERS AND POSTSECONDARY EDUCATION

24. When did you begin to talk with your parent(s) about what to do after high school?

- ◯ Sixth grade or earlier (1)
- ◯ Seventh grade (2)
- ◯ Eighth grade (3)
- ◯ Ninth grade (4)
- ◯ Tenth grade (5)
- ◯ Eleventh grade (6)
- ◯ Twelfth grade (7)
- ◯ I haven't talked with my parent(s) about my plans (8)

25. When did you <u>first</u> receive information about:

	Careers	Postsecondary Education
Sixth grade or earlier (1)	◯	◯
Seventh grade (2)	◯	◯
Eighth grade (3)	◯	◯
Ninth grade (4)	◯	◯
Tenth grade (5)	◯	◯
Eleventh grade (6)	◯	◯
Twelfth grade (7)	◯	◯
I did not receive information (8)	◯	◯

26. How early do you think you would have benefited from receiving information about careers and postsecondary education?

- ◯ Sixth grade or earlier (1)
- ◯ Seventh grade (2)
- ◯ Eighth grade (3)
- ◯ Ninth grade (4)
- ◯ Tenth grade (5)
- ◯ Eleventh grade (6)
- ◯ Twelfth grade (7)

27. Please mark <u>all</u> the sources from which you received career and postsecondary education information.

- ◯ Elementary school counselor/teacher(s) (1)
- ◯ Middle school counselor/teacher(s) (2)
- ◯ High school guidance counselor(s)/school counselor(s) (3)
- ◯ High school teacher(s) (4)
- ◯ Career and Technical Education Center staff (5)
- ◯ New Hampshire Higher Education Assistance Foundation (The NHHEAF Network Organizations) (6)

Question #27 continued

- ◯ The NHHEAF Network Organizations' Web site (7)
- ◯ Destination College event by The NHHEAF Network Organizations (8)
- ◯ Center for College Planning at The NHHEAF Network Organizations (9)
- ◯ Joe College by The NHHEAF Network Organizations (10)
- ◯ Colleges (via mail, college fairs, etc.) (11)
- ◯ My parent(s) (12)
- ◯ Local business(es) (13)
- ◯ Other Web sites (14)
- ◯ Other computer programs (15)
- ◯ Friends or relatives (16)
- ◯ Military (17)

28. How helpful was the career and postsecondary education information you received from your high school?

- ◯ Very helpful (1)
- ◯ Somewhat helpful (2)
- ◯ Not helpful (3)
- ◯ Did not receive any information (4)

29. Please mark <u>all</u> the options below that would have made the information more useful.

- ◯ More one-on-one counseling (1)
- ◯ More brochures or written information (2)
- ◯ More timely information (3)
- ◯ Better information (4)
- ◯ More online information (5)

YOUR FUTURE PLANS

30. Do you <u>plan</u> to live in New Hampshire after you complete your education?

◯ Yes (1) ◯ No (2)

31. What is the highest level of education you plan to complete?

- ◯ High school diploma (1)
- ◯ A specialized training program at a technical, business, or trade school of less than two years (2)
- ◯ Associate's Degree—2 years (3)
- ◯ Bachelor's Degree—4 years (4)
- ◯ Master's Degree (5)
- ◯ Doctorate or professional degree (6)
- ◯ Other (7)
- ◯ Undecided (8)

32. Using the choices below, please indicate the statement that comes closest to describing what <u>your parent(s)</u> feel you should do this fall after you graduate from high school.
(Please mark only <u>one</u> choice.)

- ◯ Attend a 4-year college (1)
- ◯ Attend a 2-year college (2)
- ◯ Attend a 2-year college and then transfer to another institution (3)
- ◯ Attend a postgraduate program at a prep school (4)
- ◯ Attend a vocational, technical, business, or trade school of less than two years (5)

Question #32 continued

- ◯ Become a full-time homemaker (6)
- ◯ Get a full-time job (7)
- ◯ Participate in a registered apprenticeship (8)
- ◯ Join the military (9)
- ◯ They have no strong feelings (10)
- ◯ They want me to do what I want to do (11)

33. Have you applied for admission to a college, university, or business, trade, or vocational school?

◯ Yes (1) ◯ No (2) ◯ Don't know (3)

34. Using the choices below, please indicate what you are most likely to do this fall after you graduate from high school.
(Please mark only one choice.)

- ◯ Attend a 4-year college (1)
- ◯ Attend a 2-year college (2)
- ◯ Attend a 2-year college and then transfer to another institution (3)
- ◯ Attend a postgraduate program at a prep school (4)
- ◯ Attend a vocational, technical, business, or trade school of less than two years (5)
- ◯ Become a full-time homemaker (6)
- ◯ Get a full-time job (7)
- ◯ Participate in a registered apprenticeship (8)
- ◯ Join the military (9)
- ◯ Take some time off, then decide (10)
- ◯ Join AmeriCorps/VISTA or other full-time community service program (11)
- ◯ Start my own business (12)
- ◯ Don't know (13)

SPECIAL INSTRUCTIONS

In question 34, *if you answered*:

- Attend a 4-year college
- Attend a 2-year college
- Attend a 2-year college and then transfer to another institution
- Attend a vocational, technical, business, or trade school of less than two years

Go to Section C on Page 6

If you did not answer one of the above,
Go to Section B below

Section B

This section is for those students who *are not* planning to attend a college or a prep school, vocational, technical, business, or trade school in the fall of 2007. If you answer this section of the survey, *do not* answer Section C.

YOUR CAREER PLANS

35. Which of the following best describes what your future educational or job training plans might be?
(Please mark only one choice.)

- ◯ Attend a 4-year college (1)
- ◯ Attend a 2-year college (2)
- ◯ Enter a specialized training program at a technical, business, or trade school of two years or less (3)

Question #35 continued

- ◯ Participate in an apprenticeship/internship (4)
- ◯ Obtain on-the-job training (5)
- ◯ Enroll in a training program in the military (6)
- ◯ I don't plan to continue my education (7)
- ◯ Undecided (8)

36. When do you plan to continue your education or job training?

- ◯ In January of 2008 (1)
- ◯ By the fall of 2008 (2)
- ◯ After the fall of 2008 (3)
- ◯ I'm not sure when I will continue (4)

37. Do you have a job lined up after graduation from high school?

- ◯ Yes, full-time job (1)
- ◯ Yes, part-time job (2)
- ◯ No (3)

38. Has your school provided you with an opportunity to get in touch with agencies or individuals who can help you with:

A. Getting more education or training after high school?	◯ Yes (1)	◯ No (2)
B. Finding a job?	◯ Yes (1)	◯ No (2)
C. Finding a place to live?	◯ Yes (1)	◯ No (2)
D. Getting around in your community and using community resources?	◯ Yes (1)	◯ No (2)

39. Please indicate the category that most closely represents the occupation you plan to pursue this fall and in ten years.

In fall of 2007	In ten years:	
◯	◯	Architecture and/or Engineering (1)
◯	◯	Arts, Design, Entertainment, Sports, and/or Media (2)
◯	◯	Building and Grounds Cleaning and/or Maintenance (3)
◯	◯	Business and/or Financial Operations (4)
◯	◯	Community and/or Social Service (5)
◯	◯	Computer and/or Mathematical (6)
◯	◯	Construction and/or Mining (7)
◯	◯	Education, Training, and/or Library (8)
◯	◯	Farming, Fishing, and/or Forestry (9)
◯	◯	Food Prep and/or Serving (10)
◯	◯	Healthcare (11)
◯	◯	Maintenance, Repair, and/or Installation (12)
◯	◯	Legal (13)
◯	◯	Life, Physical, and/or Social Sciences (14)
◯	◯	Management Occupations (15)
◯	◯	Military (16)
◯	◯	Office and Administrative Support (17)
◯	◯	Personal Care and Service (18)
◯	◯	Production (19)
◯	◯	Police and/or Protective Service (20)
◯	◯	Sales and Related (21)
◯	◯	Transportation and/or Material Moving (22)
◯	◯	Undecided (23)

40. If you have a job lined up after high school, how did you learn the skills you will use on the job?
(Please mark all that apply.)

- ○ High school program (1)
- ○ Volunteer work sponsored by high school (2)
- ○ Volunteer work acquired by own initiative (3)
- ○ From a current or former job (4)
- ○ Friend/coworker/family member taught me (5)
- ○ Apprenticeship/internship (6)
- ○ Vocational/technical program (7)

41. When did you decide to pursue activities other than education immediately after high school?

- ○ Sixth grade or earlier (1)
- ○ Seventh grade (2)
- ○ Eighth grade (3)
- ○ Ninth grade (4)
- ○ Tenth grade (5)
- ○ Eleventh grade (6)
- ○ Twelfth grade (7)

42. Please rate how important the following reasons were in your decision not to continue your education immediately after high school.

	Very Important	Somewhat Important	Not Important
A. I need a break from school	○	○	○
B. I can't afford to continue my education	○	○	○
C. I want/need to work to support myself	○	○	○
D. I plan to get married/start a family	○	○	○
E. I don't need to continue my education to get the job I want	○	○	○
F. I participated in a registered apprenticeship	○	○	○
G. I am joining the military	○	○	○
H. I can always continue my education in the future	○	○	○
I. I want to travel	○	○	○
J. My grades are too low	○	○	○
K. I am unsure of my plans/goals	○	○	○

43. Which of the reasons listed in Question 42 was the most important reason for not continuing your education?
(Please mark only one reason.)

○ A ○ C ○ E ○ G ○ I ○ K
○ B ○ D ○ F ○ H ○ J

44. If you marked Question 42, "I can't afford to continue my education" as an important reason in your decision to pursue other activities, please mark all statements below that apply to your decision.

- ○ My family cannot contribute enough money toward my education
- ○ My family will not contribute enough money toward my education
- ○ I don't want to assume the loan debt necessary to continue my education
- ○ I assumed I wouldn't be eligible for financial aid and didn't apply
- ○ I applied for financial aid and didn't receive enough

Section C

This section is for those students who *are* planning to continue their education on a full-time or part-time basis in the fall of 2007. If you answer this section of the survey, *do not* answer Section B.

YOUR EDUCATIONAL PLANS

45. When did you decide to continue your education after high school?

- ○ Sixth grade or earlier (1)
- ○ Seventh grade (2)
- ○ Eighth grade (3)
- ○ Ninth grade (4)
- ○ Tenth grade (5)
- ○ Eleventh grade (6)
- ○ Twelfth grade (7)
- ○ I have always known I would continue my education (8)

46. If you plan to attend a school in New Hampshire, please indicate the school you are most likely to attend.

- ○ Chester College of New England (1)
- ○ Colby-Sawyer College (2)
- ○ Daniel Webster College (3)
- ○ Dartmouth College (4)
- ○ Franklin Pierce College (5)
- ○ Granite State College (6)
- ○ Hesser College (7)
- ○ Keene State College (8)
- ○ Lebanon College (9)
- ○ Magdalen College (10)
- ○ McIntosh College (11)
- ○ New England College (12)
- ○ New Hampshire Institute of Art (13)
- ○ NHCTC Berlin (14)
- ○ NHCTC Claremont (15)
- ○ NHCTC Laconia (16)
- ○ NHCTC Manchester (17)
- ○ NHCTC Nashua (18)
- ○ NHCTC Stratham (19)
- ○ NH Technical Institute (20)
- ○ Plymouth State University (21)
- ○ Rivier College (22)
- ○ Saint Anselm College (23)
- ○ Saint Joseph School of Practical Nursing (24)
- ○ Southern New Hampshire University (25)
- ○ Thomas More College of Liberal Arts (26)
- ○ University of New Hampshire — Durham (27)
- ○ University of New Hampshire — Manchester (28)
- ○ Cosmetology school (29)
- ○ Other New Hampshire school (30)

47. If not planning to attend a school in New Hampshire, where is your school located?

○ AL (1)	○ CT (7)	○ ID (13)	○ LA (19)	○ MS (25)
○ AK (2)	○ DE (8)	○ IL (14)	○ ME (20)	○ MO (26)
○ AZ (3)	○ DC (9)	○ IN (15)	○ MD (21)	○ MT (27)
○ AR (4)	○ FL (10)	○ IA (16)	○ MA (22)	○ NE (28)
○ CA (5)	○ GA (11)	○ KS (17)	○ MI (23)	○ NV (29)
○ CO (6)	○ HI (12)	○ KY (18)	○ MN (24)	○ NJ (30)

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Question #47 continued

○ NM (31) ○ NY (32) ○ NC (33) ○ ND (34) ○ OH (35)
○ OK (36) ○ OR (37) ○ PA (38) ○ RI (39) ○ SC (40)
○ SD (41) ○ TN (42) ○ TX (43) ○ UT (44) ○ VT (45)
○ VA (46) ○ WA (47) ○ WV (48) ○ WI (49) ○ WY (50)
○ U.S. Territory or Foreign Country (51)

48a. That school is:
○ 4-year
○ 2-year
○ Less than 2-year

48b.
○ Public (state)
○ Private

49. Do you plan to attend:
○ full time (1) ○ part time (2)

50. Please indicate the category that most closely represents the major field of study you plan to pursue.

○ Agriculture & Natural Resources (1)
○ Architecture & related programs (2)
○ Aviation (3)
○ Biological & Life Studies (4)
○ Business (5)
○ Communications (6)
○ Computer & Information Technologies (7)
○ Construction (8)
○ Consumer Sciences (9)
○ Education (10)
○ Engineering (11)
○ English & Literature (12)
○ Ethnic & Cultural Studies (13)
○ Foreign Language (14)
○ Health Professions (15)
○ Hotels & Restaurants (16)
○ Law & Legal Studies (17)
○ Liberal Arts & Humanities (18)
○ Mathematics (19)
○ Mechanics & Repairers (20)
○ Parks, Recreation, & Fitness (21)
○ Physical Sciences (22)
○ Protective Services (23)
○ Psychology (24)
○ Public Administration (25)
○ Religion & Philosophy (26)
○ Social Sciences & History (27)
○ Visual & Performing Arts (28)
○ Undecided (29)

51. How many hours per week do you expect to work while enrolled in college?
○ None, do not plan to work (1)
○ 5 or fewer (2)
○ 6–10 (3)
○ 11–20 (4)
○ 21–30 (5)
○ 31–40 (6)
○ 40 or more (7)

52. Please rate how important the following factors were in your selection of the school you are most likely to attend.

	Very Important	Somewhat Important	Not Important
A. It offers the best education in my field of interest	○	○	○
B. It is affordable	○	○	○
C. It is close to home	○	○	○
D. It is the right size school for me	○	○	○
E. I have already been admitted there or believe I will be	○	○	○
F. I believe I can get financial aid there	○	○	○
G. It is far enough from home so I'll feel more on my own	○	○	○
H. It has a good reputation for its social activities	○	○	○
I. My parent(s) like it	○	○	○
J. My counselor or teacher advised me	○	○	○
K. My friends are likely to attend	○	○	○
L. It has a very good academic reputation	○	○	○
M. It offers unique education programs	○	○	○
N. Its graduates gain admission to top graduate/professional schools	○	○	○
O. Its graduates get good jobs	○	○	○

Question #52 continued

	Very Important	Somewhat Important	Not Important
P. I was attracted by the religious affiliation/orientation of the school	○	○	○
Q. Its rankings in national magazines	○	○	○
R. Its reputation for athletic and/or extracurricular activities	○	○	○

53. Which of the factors listed in Question 52 was the most important factor in your selection of a school?
(Please mark only one factor.)
○ A ○ B ○ C ○ D ○ E ○ F ○ G ○ H ○ I ○ J ○ K ○ L ○ M ○ N ○ O ○ P ○ Q ○ R

54. Are you planning to attend your first-choice school?
○ Yes (1) ○ No (2)

55. If you will not be attending your first-choice school, which reason below is the most important reason for your decision not to attend it?
(Please mark only one factor.)
○ It is too far from home (1)
○ It is too expensive (2)
○ My parent(s) discouraged me (3)
○ I wasn't accepted (4)
○ I didn't get enough financial aid there (5)
○ I changed my major/program (6)

56. If you will not be attending a USNH (UNH, Plymouth State University, Keene State College, or Granite State College) institution, which reason is the most important reason for your decision not to attend?
(Please mark only one factor.)
○ I was not accepted (1)
○ My major is not offered (2)
○ The cost of attendance is too high (3)
○ I want to study out-of-state (4)
○ It is not the right size school for me (5)
○ I got more financial aid at my institution (6)
○ My institution has a better academic reputation (7)
○ It is not the right location for me (8)
○ Other reason (9)

57. If you will not be attending a NHCTCS (NHTI, Berlin, Claremont, Laconia, Manchester, Nashua, Stratham, or an affiliated local academic center) institution, which reason is the most important reason for your decision not to attend?
(Please mark only one factor.)
○ I was not accepted (1)
○ My major is not offered (2)
○ The cost of attendance is too high (3)
○ I want to study out-of-state (4)
○ It is not the right size school for me (5)
○ I got more financial aid at my institution (6)
○ My institution has a better academic reputation (7)
○ It is not the right location for me (8)
○ Other reason (9)

58. **If you will not be attending another institution in New Hampshire, which reason is the most important reason for your decision not to attend?**
(Please mark only one factor.)
- ○ I was not accepted (1)
- ○ My major is not offered (2)
- ○ The cost of attendance is too high (3)
- ○ I want to study out-of-state (4)
- ○ It is not the right size school for me (5)
- ○ I got more financial aid at my institution (6)
- ○ My institution has a better academic reputation (7)
- ○ It is not the right location for me (8)
- ○ Other reason (9)

59. **Do you have any concern about your ability to finance your college education?**
(Please mark only one.)
- ○ None (I am confident that I will have sufficient funds) (1)
- ○ Some (but probably will have enough funds) (2)
- ○ Major (not sure I will have enough funds to complete college) (3)

Section D

THIS SECTION IS FOR THOSE STUDENTS WHO ATTENDED CAREER AND TECHNICAL EDUCATION (CTE) PROGRAMS (VOCATIONAL OR TECHNICAL TRAINING COURSES).

60. **Which Career and Technical Education (CTE) Center, from the list below, did you attend?**
- ○ Berlin Vocational Center (1)
- ○ Cheshire Center of Applied Science & Technology — Keene (2)
- ○ Concord Regional Technology Center (3)
- ○ Con-Val High School — Peterborough (4)
- ○ Creteau Regional Technology Center — Rochester (5)
- ○ Dover Vocational Center (6)
- ○ Hartford Area Career & Technical Center — Hartford, VT (7)
- ○ Hugh J. Gallen Regional Vocational Center — Littleton (8)
- ○ J. Oliva Huot Technical Center — Laconia (9)
- ○ Manchester School of Technology (10)
- ○ Milford HS & Applied Technology Center (11)
- ○ Nashua Senior High School (12)
- ○ Pembroke Academy (13)
- ○ Pinkerton Academy — Derry (14)
- ○ Plymouth Regional Technical Center (15)
- ○ Portsmouth Senior High School (16)
- ○ Region 6 Career & Technical Center — Conway (17)
- ○ Region 9 Vocational Technical Center — Wolfeboro (18)
- ○ River Bend Career & Technical Center — Bradford, VT (19)
- ○ Salem High School Vocational Center (20)
- ○ Seacoast School of Technology — Exeter (21)
- ○ Somersworth Regional Vocational Center (22)
- ○ Sugar River Valley — Claremont (23)
- ○ Sugar River Valley — Newport (24)
- ○ White Mountains Regional High School — Whitefield (25)

PLEASE DO NOT WRITE IN THIS AREA

Question #60 continued
- ○ Wilbur H. Palmer Voc. Tech. Center — Hudson (26)
- ○ Winnisquam Regional High School — Tilton (27)

61. **When were you first informed about the opportunities available at your regional CTE Center?**
- ○ Seventh grade or earlier (1)
- ○ Eighth grade (2)
- ○ Ninth grade (3)
- ○ Tenth grade (4)
- ○ Eleventh grade (5)
- ○ Twelfth grade (6)

62. **Between grades 7 and 11, how often were you presented with information about your regional CTE Center?**
- ○ Once (1)
- ○ Twice (2)
- ○ Three times (3)
- ○ Four times (4)
- ○ Five times (5)
- ○ Six or more times (6)

63. **Did you have the opportunity to participate in a technical student organization (DECA, FBLA, FCCLA, FFA, HOSA, Skills USA, VICA, TSA)?**
- ○ Yes (1)
- ○ No (2)

64. **If you did participate in a student organization, did the skills you learned there help you in your area of technical skill development?**
- ○ Yes (1)
- ○ No (2)

65. **Please rate how much you agree with each of the following statements.**

	Strongly Agree	Agree	Disagree	Strongly Disagree
A. My CTE education will provide me with significant technical skill training.	○	○	○	○
B. My CTE education will provide me with the support I need to be successful in applied academics at technical schools (e.g., reading manuals).	○	○	○	○
C. My CTE education will help me get a job.	○	○	○	○
D. My classes have usually been interesting.	○	○	○	○
E. My CTE education will provide me with the support I need to transition from high school to a career.	○	○	○	○
F. My CTE education will help me find and go on to postsecondary education or training.	○	○	○	○
G. My CTE education will provide me with the support I need to transition from high school to postsecondary education or training.	○	○	○	○
H. In the next six months I will be working or studying in a field related to my CTE program.	○	○	○	○

Thank you for completing this survey!

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