# CHOOSING AN UNDERGRADUATE STEM MAJOR: FAMILY SOCIOECONOMIC STATUS, INDIVIDUAL, AND INSTITUTIONAL FACTORS

By

LIAN NIU

A DISSERTATION PRESENTED TO THE GRADUATE SCHOOL
OF THE UNIVERSITY OF FLORIDA IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

UNIVERSITY OF FLORIDA

2013

## ACKNOWLEDGMENTS

This dissertation is based upon work supported by the Association for Institutional Research, the National Science Foundation, the National Center for Education Statistics, and the National Postsecondary Education Cooperative under Association for Institutional Research Grant Number DG12-81. Any opinions, findings, and conclusions or recommendations expressed in this dissertation are those of the author and do not necessarily reflect the views of the Association for Institutional Research, the National Science Foundation, the National Center for Education Statistics or the National Postsecondary Education Cooperative.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Abstract

Promoting STEM enrollment in higher education has been a focus of national educational discussion and policy. This study examined an important yet understudied part of the STEM pipeline in college, namely factors that impact the decision making in STEM enrollment. Adopting the theories of human capital and rational choice, this study investigated the STEM enrollment pattern with a focus on students' family socioeconomic background. The purpose of the study was to examine whether STEM enrollment is systematically correlated to students' family SES background. The following questions guided the study: 1) Is students' family SES related to their decision of whether to enroll in a STEM major in college? 2) Does the enrollment decision in STEM fields vary for students with different college investment levels? 3) Does the enrollment decision in STEM fields vary at institutions with different scales and levels of STEM major offerings? It was hypothesized that STEM enrollment probability is negatively correlated to family SES, positively correlated to college investment, and varies with the level and scale of STEM offering at the institution where students enroll.

Results show that family SES by itself is not statistically significantly correlated to STEM enrollment. College cost is negatively correlated to STEM enrollment. STEM enrollment does vary with the level and scale of STEM offering at the institution one is enrolled at. The assumptions based on the conceptual framework are not supported by the findings. However, family SES does interact with gender, race, academic preparation, and STEM offering level at institution in correlation with STEM enrollment. Lower SES students tend to make STEM decisions that are not aligned with their academic preparation level. Overall, family SES strengthens the magnitude of the

factors that are positively correlated with STEM enrollment, and reduces the magnitude of those that are negatively correlated with STEM enrollment.

Findings show that lower SES students are disadvantaged in STEM enrollment in college, even after controlling for important predictors of STEM enrollment such as academic preparation and demographic characteristics.  Educators should provide lower SES students with more information about STEM majors in order to improve STEM enrollment in higher education.

CHAPTER 1
INTRODUCTION

## Problem Statement

Educating a strong workforce in science, technology, engineering, and math (STEM) fields is considered crucial for the United States to retain its global leadership position in a science and technology dominated global economy (Committee on Equal Opportunities in Science and Engineering, 2004). The country's strengths in STEM education in postsecondary settings have propelled strong economic performance, led to the development of innovative industries, and produced good jobs for its people (President's Council of Advisors on Science and Technology, 2012). Training STEM professionals not only benefits the economy; it also has important bearings on literacy and democracy (President's Council of Advisors on Science and Technology, 2012).

An examination of college enrollment statistics in STEM majors shows that the current enrollment level may be insufficient to meet the nation's human resource needs in STEM fields. If the current rate of STEM degree production continues, predictions suggest that there will be a gap of 1 million STEM professionals between what the nation's economy needs and what the colleges and universities deliver over the next decade (President's Council of Advisors on Science and Technology, 2012). Exemplifying this dilemma, it has been shown that the employment in STEM fields increased 23 percent between 1994 and 2003, while college graduates in STEM fields increased only eight percent from academic year 1994-1995 to 2002-2003 (United States Government Accountability Office, 2005). From academic year 1995-1996 to 2003-2004, the percentage of students in STEM majors increased only 2 percent, from 21 to 23 percent, while from academic year 1994-1995 to 2002-2003, the number of graduates in non-STEM fields increased 30 percent (United States Government Accountability Office, 2005). From academic year 1995-1996 to 2003-2004, the numbers of international students in STEM fields on the Bachelor's level increased 339 percent (United States Government Accountability Office, 2005). International students' share in Master's and doctoral degree continues to increase from academic year 1994-1995 to 2002-2003. These students earned more than 30 percent of Master's degrees in engineering, mathematics/computer sciences, and physical sciences and more than 30 percent of doctoral degrees in all STEM fields except for agricultural/biological sciences and psychology (United States Government Accountability Office, 2005). Thus, there is a need to improve the production of STEM majors among domestic students'.

Numerous studies have investigated students' enrollment and success in STEM majors (Chen & Weko, 2009; Crisp, Nora, & Taggart, 2009; Griffith, 2010; Harper, 2010; Hurtado, Newman, Tran, & Chang, 2010; Malcom, 2010; National Science Foundation, 2007; Pender, Marcotte, Domingo, & Maton, 2010; Perna, Gasman, Gary, Lundy-Wagner, & Drezner, 2010; Rask, 2010). Researchers have focused on gender and race/ethnicity disparities in STEM enrollment, as well as the retention of STEM students (Griffith, 2010; Malcom, 2010; Rask, 2010). Empirical evidence has shown that there are gender and race/ethnicity gaps in STEM fields in colleges, overall favoring white male (Maple & Stage, 1991; Riegel-Crumb & King, 2010; Smyth & McArdle, 2004). Asian students are overrepresented in STEM majors, while Hispanic, African American, and Native American students are underrepresented (National Science Foundation, 2007).

The persistence of STEM students has also been widely discussed. The leak of the STEM pipeline in college has been a reoccurring problem for educators and policy makers. Considerably large numbers of students who initially choose to enroll in STEM majors later decide to leave STEM fields. Among students who first enrolled in physical sciences or computer/information sciences in 2003-2004, only 35.4% and 48.1% have obtained Bachelor’s degree in their original major field by 2009, respectively (President's Council of Advisors on Science and Technology, 2012). On the other hand, 65.7% of the students who first enrolled in social sciences and 82.9% of those in other non-STEM fields in 2003-2004 persisted to obtain Bachelor’s degree, respectively. Studies that have investigated students’ departure from science related majors have revealed that uninformed decision making and practical concerns cause students to leave STEM majors. For example, conflict between financial burden students carry and the demanding workload of science related majors lead to departure from these majors (Seymour & Hewitt, 1997).

The higher education pipeline consists of a sequence of decisions and actions (St. John, Asker, & Hu, 2001), from the formation of aspiration to attend college, submitting college application, making college choice, to selecting major and deciding whether to persist. Similarly, the STEM education pipeline consists of several processes that eventually lead students to STEM degrees. While the persistence in STEM fields has been examined repeatedly (Espinosa, 2009; Griffith, 2010; Price, 2010), less attention has been paid to how in general college students choose to enter or avoid STEM fields. Although the issue of STEM enrollment pattern has long been an important topic for educational researchers, the focus of such investigation has been almost exclusively on the dimensions of gender and race/ethnicity (Dickson, 2010; Frehill, 1997; Turner & Bowen, 1999; Ware & Lee, 1988).

The importance of gender and race related factors in students' educational decision making is significant (Smyth & McArdle, 2004; Thompson, 2003; Trusty, Robinson, Plata, & Ng, 2000). However, gender and race are not the only factors that influence students' decisions regarding STEM enrollment, nor are they the only sources of inequalities in STEM enrollment in college. The process of choosing college major is "seemingly voluntary" (Correll, 2001, p. 1692); however, it is influenced by numerous factors ranging from role models (Hackett, 1989) to students' values (Mitchell, 2008). Thus, the process of choosing a major is beyond the act of making decisions based solely on personal interests or identities developed through socialization. Since all societies are stratified and stratification in the society influences inequalities in education (Cole & Cole, 1973; Sianou-Kyrgiou, 2009), understanding the relationship between the main dimensions of stratification in the larger society and educational phenomena is the key to finding out why certain educational phenomena happen and how to promote changes in desirable directions. In the American society, gender, race, and class are the three major social stratification dimensions (Mixon, 2007). Correspondingly, gender, race/ethnicity, and socioeconomic status (SES) have been the main dimensions of investigation in educational equity research (Anderson & Hearn, 1992). While efforts have been made in promoting higher education access and success for low-income students, the dimension of SES has been oftentimes ignored in both public discussion and scholarly research of STEM education. The neglect of SES as an indicator warrants further attention in the research literature.

SES should not be ignored in STEM enrollment pattern research because although gender and race/ethnicity factors are inevitably entangled with SES issues, they are different dimensions of stratification. For each dimension, a certain pattern between this dimension and STEM enrollment may hold across levels of the other dimensions. For example, gender differences in STEM enrollment may hold across different racial/ethnic groups, and vice versa. Similarly, it is plausible that a certain relationship exists between students' SES and their decision of STEM enrollment in college that holds for both genders and various racial/ethnic groups. Recognizing the importance of SES as an independent dimension of stratification in higher education is likely to lead to greater insight into the educational phenomena regarding STEM enrollment that we observe.

SES should be examined in the investigation of STEM enrollment pattern also because of the economic value of STEM majors. While the economic value of higher education has long been widely discussed and recognized, it has rarely been related to students' choice of STEM majors in college. Higher education is a public good, bringing return for public investment, strengthening the national economy, and exerting economic impact on communities where higher education institutions are located. At the same time, higher education is also a private good. The economic return of college education for individuals is significant, suggesting that private investment of money and time in college education is wise for most people (Leslie & Brinkman, 1988). College education also brings nonmonetary returns, such as better health and higher life quality (Baum, Ma, & Payea, 2010).

The significance of higher education's economic value is well recognized by individuals making educational decisions. Students' financial expectations weigh heavily in their higher education choices (Leslie & Brinkman, 1988). For example, economic motives, such as earning job credentials, learning a skill, and making money, were listed about 3.5 times as frequently as noneconomic motives by high school seniors as determinant of college attendance (Leslie, Johnson, & Carlson, 1977). In the 2009 national survey of college freshmen, "to be able to get a better job" was cited by 84 percent of students as a "very important" reason of deciding to attend college, the highest among all reasons, while "to be able to make more money" was listed by 73 percent of students as a "very important" reason for attending college (Pryor, Hurtado, DeAngelo, Blake, & Tran, 2009).

The fact that individuals tend to base their college attendance decisions at least partly on economic return rate of college education (Mattila, 1982) suggests that the economic value of college majors should be taken into account when examining students' enrollment pattern in different majors. In this respect, STEM majors distinguish themselves from other undergraduate majors significantly. In general, STEM majors provide higher financial rewards and better job security upon graduation as compared to other majors (Economics and Statistics Administration, 2011). Research has shown that STEM majors expect the highest starting salaries (McMahon & Wagner, 1981; Rampell, 2011). Berger (1992) finds that while salaries fluctuate over time, STEM majors' salaries remain the most stable while the salaries of business and liberal arts majors vary over time the most; engineering jobs are paid the highest, followed by sciences. Wage difference continues throughout early career stage, with science and engineering always being high-paying occupations (Solmon, 1981). Besides relatively high and stable financial rewards, STEM fields also tend to lead to high occupational status (Cole & Cole, 1973). The prominence of engineers in the society has been recognized as early as at the beginning of the $20^{th}$ century (Gross, 1969). In the American occupation structure, scientific and engineering occupations have long been ranked at the top (Blau & Duncan, 1967).

Making educational decisions, such as choosing a college major, is an interaction between the higher education system and the students. The higher education system provides study options, for example, different majors, that lead to different financial rewards as one type of return of college education. Students make educational decisions based on their own contextual constraints (St. John, Asker, & Hu, 2001). To respond to the economic value of different majors, students evaluate their own contextual constraints, such as financial means and other related characteristics to reach a decision. The nature of college education as a personal investment good and the financial rewards difference among college majors form a dynamic relationship between the higher education system and the students.

While many factors may contribute to students' financial means, such as receiving financial aid or holding part-time job, the deciding factor in this respect is students' family SES. Family contribution to higher educational costs is the primary financial resources students rely on (Horn, Chen, & Chapman, 2003). The higher the family SES, the more affordable college becomes for students. The opposite holds true as well. Therefore, when evaluating their own contextual constraints, students' decisions of college education inevitably are limited by their family SES and expected family contribution, among other factors. While it is generally agreed that family SES exerts significant influences on higher education outcomes both directly and indirectly (Kahlenberg, 2004; Kincheloe & Steinberg, 2007), the plausible linkage between family SES and college major choice pattern has not received much attention. Empirical evidence suggests that family SES is related to college major choice in that students from varied SES backgrounds tend to have different preferences for college majors based on types of rewards, with some value financial rewards while others value cultural rewards (Ma, 2009). Whether there is systematic association between students' family SES and their decision of STEM enrollment at the national level, however, is still unclear.

## Purpose of the Study

Considering the economic value of STEM majors and the contextual constraints of students' family SES, it is plausible that family SES plays a systematical role in STEM enrollment decision. The purpose of this study was to examine college students' enrollment decision in STEM majors with a focus on students' family SES. This study examined whether there is systematic association between students' family SES and their enrollment in STEM majors and if so, what the direction and magnitude of the association is. The overarching research question that guided this study was: Do the enrollment in STEM majors vary for students with different family SES background?

In the current higher education research literature, investigation of STEM enrollment from the SES perspective suffers from both low quantity and contradictory findings. As discussed above, most attention has been placed on the enrollment of gender and racial/ethnic groups. Of those studies that explore the topic from the SES perspective, findings are either based on data from decades ago, or are contradictory to each other about the direction of the association between family SES and major choice pattern. For example, Ware and Lee (1988) find that male students from high SES background are more likely to enroll in science majors, while Ma (2009) concludes that students from high SES families are more likely to choose culturally intensive yet non-lucrative majors such as humanities.

This study adopted the theory of human capital to conceptualize the relationship between family SES and STEM enrollment. According to human capital theory, human capital is a means of production, meaning that additional investment could yield additional output, or productivity (Becker, 1993). “Education and training are the most important investments in human capital” (Becker, 1993, p. 17). Human capital theory argues that education is an important activity of human investment that increases human capacities by improving the qualitative dimension of human resources; therefore, additional education explains rise in individuals’ income (Schultz, 1961).

Built within the framework of investment-output, human capital theory emphasizes the relation between education cost (investment) and economic return of education (output). The cost of education comprises not only the cost of providing education, but also the income that is foregone by students while receiving education (Schultz, 1961). Since education is seen as a form of investment in individual’s skills and productivity, the monetary cost of receiving education, besides time and efforts, becomes part of the investment students make in themselves. Such investment is expected to yield financial return, among other forms of benefits in the long run (Leslie & Brinkman, 1988).

Related to human capital theory is the notion of rational behavior, or rational choice. According to rational choice theory, individuals act rationally based on their personal preferences rather than on other people's wishes. Therefore, the standard for being rational varies for different people. The concept of rational behavior has been frequently applied to educational research, mainly in the exploration of student decision making. Issues include how much education to acquire, which higher education institution to attend, and whether to complete higher education (DesJardins & Toutkoushian, 2005).

Based on human capital theory, to increase earnings, students would want to invest more in their education in order to improve their productivity and eventually earn high income. However, because of the contextual constraints each student finds himself or herself in (St. John, Asker, & Hu, 2001), students must also consider how much cost is involved and whether such cost is affordable. Assuming that students act rationally in choosing college major, achieving a balance between investment and affordability and between investment and return is crucial to decision making. Students from different SES backgrounds can afford different level of higher education investment and may have different understandings and expectations of the return of college education, be it financial, cultural, or personal. Such concern might influence students' choice of study field in college based on their family SES, which determines the level of education investment they can afford. Students from low SES families might want to maximize the financial return of the investment in a college education while minimizing the investment in terms of direct monetary input and time, since the latter is linked to foregone income. Since the time investment (4 years for a Bachelor's degree) and monetary investment (tuition, fees, accommodation, and other costs related to attending college within any given institution) are similar for different undergraduate majors, a relatively more lucrative study field, which has better potential for higher income with relatively low investment, may be especially desirable for students from low SES families. Whether this is what happens in the general student population remains to be explored.

## Research Questions

Specifically, this study addressed the following research questions: (1) Is students' family SES related to their decision of whether to enroll in a STEM major in college? (2) Does the enrollment decision in STEM fields vary for students with different college investment levels? and (3) Does the enrollment decision in STEM fields vary at institutions with different scales and levels of STEM major offerings?

A series of individual and institutional factors that might be associated with STEM major choice were examined. These included individual characteristics such as pre-college academic achievements, educational aspirations, parental support, and financial constraints. Recognizing that college education decisions are not only related to personal traits, but also constrained by college characteristics and college experiences (Mau & Jepsen, 1992; Mullen, 2010), this study examined institutional factors including college type and STEM major offering. The association between family SES and STEM major decision was examined among students who differ on the above-mentioned characteristics in order to reveal possible varying STEM enrollment decisions.

## Definition of Terms

### STEM Majors

The term STEM stands for science, technology, engineering, and mathematics. In higher education, this term encompasses specific study fields defined as majors in colleges and universities. Researchers have adopted different definitions of the term STEM based on different interpretation of the term science. The broad definition includes natural sciences as well as social/behavior sciences such as sociology and psychology. The narrow definition, on the other hand, only includes natural sciences. This study adopted the narrow definition used by the National Center for Education Statistics (NCES) in its *2009 Statistics in Brief* (Chen & Weko, 2009) and excludes social/behavior sciences. In this study, STEM was defined as mathematics, natural sciences (including physical sciences and biological/agricultural sciences), engineering, and computer/information sciences.

Based on this definition, college majors as collected in the main data source of this study, ELS:2002, were classified into four categories. Appendix A provides a list of college majors and the corresponding STEM categories they fall into.

### Socioeconomic Status

Socioeconomic status, or SES, is a frequently used term in educational research that generally refers to an individual's or a family's economic and social position. Although the basic definition of SES is clear, there are various ways of measuring this construct. In educational research, variables such as family size, dwelling area, mobility, educational aspiration, and reading materials at home have been used as indicators of students' SES (White, 1982). Although these variables measure various aspects of students' family, they are more indirect than direct measures of a family's economic and social position. For example, the dwelling area is a result of a family's economic means, while presence of reading materials at home can be traced back to parents' educational level. In this study, I used the three most basic factors to measure students' family SES: family income, parents' educational level, and parents' occupation.

## Significance of the Study

This study will contribute to the higher education literature in several ways. First, it focused on a piece of STEM pipeline that has been largely missing from the existing literature, namely students' decision of STEM enrollment. Knowing what factors are related to students' STEM major decision may enable researchers and educators to discover students' concerns about STEM majors and the obstacles they may later face in completing STEM programs. Such information in turn may increase both STEM enrollment and retention. During an era when the retention rate in STEM fields is still relatively low (National Science Foundation, 2011), the findings of this study will be of practical value. Second, the study examined the major choice process by going beyond gender and racial perspectives and examining the dimension of family SES. By doing so, this study aimed to reveal general mechanism of college major choice in STEM fields across gender and racial groups. Third, this study's focus on family SES and the economic value of STEM majors for individuals was timely given the current national concern about the affordability of higher education (Alexander, Harnisch, Hurley, & Moran, 2010).

# CHAPTER 2
# REVIEW OF LITERATURE

This chapter presents an overview of college students' STEM enrollment from the perspective of socioeconomic status. Pivotal to this inquiry is understanding of the literature and theories related to STEM education in college, student decision making, and the role socioeconomic status plays in college education. This chapter is organized into three sections: 1) college student decision making; 2) research on STEM education in college; and 3) research on the association between socioeconomic status and higher education. In each part, I discuss the primary theory underlying empirical studies in that area and review the existing research. The chapter ends with the conceptual model for this study developed through an integration of the current research.

## College Student Decision Making

In the contemporary American society, individuals are, to large extent, responsible for making decisions about their own education. First, parents decide which school to send their children to. When students reach their teenage years, they make educational decisions for themselves with help from family, friends, school, and the community. From the type of school, to the level of education, to career-related study field, students and their families face choices and make decisions. At the level of tertiary education, students typically become more independent in making these decisions. As Manski and Wise (1983) argue, college choice is an individual self-selection process.

Students' decision making does not stop at choosing a college (Karen, 2002). After entering college, they still face decisions such as choice of major, whether to persist, and whether to pursue graduate education upon graduation. While different choices lead to different educational and occupational outcomes (Mullen, 2010), understanding how and why students choose to or not to pursue certain formal education is key to understanding the educational system and the larger society it serves. Over the past decades, research has explored the mechanism of students' higher educational decision making behaviors. Focus has been placed on students' decisions of college attendance, college choice, major field choice, persistence in college, and career-related choice behaviors (Arcidiacono, Hotz, & Kang, 2012; Chapman, 1981; Crisp, Nora, & Taggart, 2009; DesJardins, Dundar, & Hendel, 1999; Dickson, 2010; Eccles, 1994; Ferry, Fouad, & Smith, 2000; Hazari, Sonnert, Sadler, & Shanahan, 2010; Kinzie, Palmer, Hayek, Hossler, Jacob, & Cummings, 2004; Kurlaender, 2006; Perna, 2006; Perna & Titus, 2004; Trusty, Robinson, Plata, & Ng, 2000).

While studies differ by student population and analysis methods, several conceptual perspectives underlie most studies. John Holland's vocational choice theory (1966b) combines psychological and sociological components to integrate both the predispositions and behaviors of students and the characteristics of the institutions students attend. Rooted in economics and sociology, rational choice theories argue that individuals act "rationally" by calculating the costs and benefits of any action before making decisions about what to do (Scott, 2000). Related to rational choice theories, St. John, Asker, and Hu (2001) see student decision making as bounded by *situated contexts*. They emphasize the interaction between the contextual constraints and students' educational options (St. John et al., 2001). Human capital theory argues that college education, like other levels of formal education, is an important form of investment in individuals' human capital, which is expected to bring increased financial reward in the long run (Becker, 1993). In the following subsections, I discuss each perspective and its application in students' higher educational decision making process.

### Holland's Vocational Choice Theory

Holland's vocational choice theory, which is based on the notion of person-environment fit, is one of the most frequently cited theories in the literature of college student decision making ,. Holland's theory focuses primarily on how individuals choose vocations, and related to vocations, how college students choose fields of study. Holland develops a category of six major personality types: Realistic, Investigative, Artistic, Social, Enterprising, and Conventional (Holland, 1966b, 1997). People of different personality types possess different attitudes, interests, and competencies. For example, people of the Artistic type generally prefer the creation of art forms and products while avoiding routine activities and established rules. On the other hand, people of the Conventional type are prone to ordered and systematic activities while lacking artistic competencies. Holland argues that students choose study field based on their own personality type.

What distinguishes Holland's theory from other psychological perspectives of student decision making is that it connects individuals' personality with the environment they find themselves in. The theory develops six model environments that are characterized by traits of certain personality type. Each environment reflects the atmosphere created by people who share the same personality type and represents a certain type of social setting in the society. Certain competencies and skills and a set of standards for rewarding certain traits and activities are also emphasized within each environment. As one type of social setting, college majors are also categorized to represent each personality type. For example, engineering represents the Investigative type, while accounting represents the Conventional type (Holland, 1966a).

Holland's theory argues that an individual's personality type should be congruent with the environment. That is, people achieve the best in an environment where his or her competencies, skills, and interests are valued and his or her preferable activities are rewarded. It is assumed that individuals choose environments that fit their personality type. Through such self-selection process, individuals of the same personality type gather together and cooperate with each other. College students, therefore, are assumed to tend to choose college major and occupation that represent their own personality type. In turn, the environment of certain college major or occupation reinforces individuals' traits that are congruent with those of other people in that environment.

Because of the relevance of Holland's theory to college students' educational decision making process and its emphasis on the interaction between individuals and the environment, it has been widely adopted in investigations of college students' choice of major field and occupation. Holland personality scales have been shown to be strong predictors of college major choice among certain student population, such as at selective liberal arts college (Porter & Umbach, 2006). The theory has helped researchers establish relationship between factors such as self-esteem and internal locus of control and the choice of major field in college, suggesting that higher self-esteem is positively related to the choice of enterprising and realistic types of college majors (Song & Glick, 2004). Examination of college students' career choices reveals that factors such as gender and institutional characteristics are entangled with Holland's career models, suggesting that there are varying personal-environment fit patterns among various student groups (Flores, Robitschek, Celebi, Andersen, & Hoang, 2010). The congruence between personality type and college major type also serves as a predictor of college persistence, reinforcing the importance of the fit of personality and environment (Brackney, 1993). The assumption of congruence between personality and environment has also been useful in deciding the type of college major specialties, such as in the medical field (Borges, Savickas, & Jones, 2004).

While the congruence between personality type and environment has been repeatedly shown to be predictive of students' college major and career choices (Huang & Healy, 1997; Smith, 2010), Holland's theory of career choice is not without its limitations. Concerned about its application to higher educational setting, researchers have called into questions its validity among culturally and racially/ethnically diverse student populations (Leong, Austin, Sekaran, & Komarraju, 1998; Mobley & Slaney, 1996; Trusty, Ng, & Ray, 2000), its ignorance of the changing nature of both the individuals and the environment (Osipow & Fitzgerald, 1996), and its lack of sensitivity to gender differences (Farmer, Rotella, Anderson, & Wardrop, 1998). In a study of college major choice pattern of racial/ethnic student groups, Trusty, Ng, and Ray (2000) conclude that Holland's theoretical formulations about the effects of variables on the choice of social-type college majors and occupational environments are best supported by white students only. This finding suggests that Holland's theory may be incomplete in explaining the educational decision making of racial/ethnic minority students. As the diversity of the college student body increases in terms of demographic characteristics such as race/ethnicity, adopting this theory in college major choice research should be taken with caution.

A more general concern about the application of Holland's theory in research of college major choice refers to the fact that it only reveals part of the mechanism. The foremost underlying assumption of Holland's theory is that people tend to choose an environment that matches their own competencies, preferences, and interests. While person-environment congruence does play a role in students' decision making, the picture depicted by Holland's theory is incomplete in explaining the complex process of college major choice. Researchers have questioned whether vocational interest is the primary determinant in students' major and career choices (Leong, Austin, Sekaran, & Komarraju, 1998). Students' demographic characteristics, socioeconomic background, geographic region, cultural background, current higher education policies, as well as labor market changes may all have bearing on students' decision of which study field to enter and which career path to follow. The influence of these factors as well as possible interactions between person-environment congruence and educational, social, economic, and cultural factors should not be ignored when investigating the mechanism of college major choice. Holland's theory, while highly relevant in terms of psychological traits and congruence and provides a useful typology for describing individuals and college environments (Edwards, 2008), does not explain all the variability of college major choice. As Holland himself advocates, the examination of college student decision making should incorporate demographic, social, and educational factors as well (Holland, 1997).

## Rational Choice Theory

Unlike Holland's vocational choice theory, which emphasizes the psychological aspect of decision making, rational choice theory is rooted in economics and sociology. It models social interaction as social exchange, in which people are motivated by the benefits they will obtain from their actions. According to rational choice theory, social actions can be seen as instrumental. Individuals are motivated by their own preferences, yet at the same time act within given constraints. They make decisions in relation to both their preferences and the means for reaching their goals (Scott, 2000). Oftentimes, people follow various paths to reach a specific goal. However, different paths or actions are related to different costs and rewards. The profit, or benefit, one obtains from an interaction equals the rewards minus the costs. This requires individuals to choose from the alternatives. After considering the outcomes of alternative actions, individuals are able to make decisions about which action would maximize their benefits (Scott, 2000). Individuals act in a rational way by making decisions based on calculation of expected costs and benefits. Being "rational" here refers to taking actions that are beneficial to the individual. In this sense, even if an action may appear to be irrational for other people, as long as it is based on calculation of costs and benefits, it is seen as rational action from the perspective of rational choice theory (Scott, 2000).

Rational choice theory has been applied in educational research to examine students' decision making process. The dynamic between expected rewards and incurred costs is cited to explain the cause of misconduct such as plagiarism and driving under influence of alcohol among college students (Maple & Stage, 1991; Ogilvie & Stewart, 2010). The process of evaluating alternative actions is used to explain curricular choice among students from different social classes (Gabay-Egozi, Shavit, & Yaish, 2010). Research has shown that rational choice theory explains academic progress such as attrition (Beekhoven, de Jong, & van Hout, 2002), the relation between economic inequality and stratification in the educational system (Hansen, 2008), and different types of participation in higher education among students of varying social class (Need & de Jong, 2001).

Despite its explanatory power, the rational choice theory is not without critics. DesJardins and Toutkoushian (2005) discuss several questions about the application of rational choice theory in research on college student decision making. As discussed above, the definition of “rational” in this theory is different from the common use of the term. This has led to inconsistency of the interpretation of “rational”, which inevitably generates doubt about the validity of the theory in explaining student behaviors. Since students rarely possess all critical information about the costs and rewards of higher education, it is argued that their decisions cannot be assumed to be based on rational calculation. Even if students do make decisions based on abundant information, they may still deviate from the classic economic rational choice by reacting differently to alternatives that in effect lead to similar outcomes. The lack of consideration of moral and emotional aspects of students’ life renders the application of rational choice theory less sound. DesJardins and Toutkoushian (2005) contend that rational choice theory does not require perfect information; it only requires that individuals make decisions based on the information that they do possess. Acting rational does not mean that each individual would react to the same situation with the same behavior, but rather takes into account people’s different beliefs, preferences, and taste for risk. Furthermore, rational choice theory acknowledges the importance of the external and internal constraints that limit people's decision making behaviors, such as institutional, psychological, and cultural limitations.

The key point of understanding rational choice theory is that being rational is relative and the standard of rationality is dependent on each individual. As a result, it is difficult to decide whether individuals are acting rationally solely based on the observation of the decisions they make. To better understand students' decisions regarding their college education, a thorough consideration of their beliefs, preferences, personal, and institutional constraints is necessary. Without a proper interpretation of "rational" for different students, it would be impossible to explore the dynamic of costs and rewards in the process of decision making (Sullivan, 2006). Revealed preferences, beliefs, and desires, as well as observable constraints are channels through which rationality can be defined for individuals. In sum, rational choice theory remains a powerful perspective in explaining college students' decision making process. Although individuals' choices may appear to be irrational to other people, it is important to note that rationality is relative. When applying the theory, it is crucial to recognize that it is not necessary that individuals shall possess perfect information in order to act rationally.

**St. John's Student-Choice Construct**

The assumption that college students are rational actors in terms of higher education decision making is adopted by researchers in building theories of student choice making. St. John, Paulsen, and colleagues (Paulsen & St. John, 1997; St. John, 1994a; St. John et al., 2001; St. John, Paulsen, & Starkey, 1996) develop the notion of student-choice construct as a framework to examine the role of public policies and finances in student choice. The student-choice construct integrates both developmental and change perspectives on college student outcomes. This theoretical framework takes into account social and economic forces, educational trends and policy, as well as education and employment opportunities that influence students' decision making. The student-choice construct also emphasizes the examination of the effects of public policy across student outcomes and in different contexts. The first principle of the construct is that the choice of college major is one of the decisions that students make within a sequence of choices regarding their higher education. This decision making sequence generally consists of identifying postsecondary and career aspirations, the choice to attend college, the choice of college, the choice and possible change of college major, decision about persistence in college, and the decision regarding graduate education. The accumulation of student-choice processes results in overall student attainment.

Another basic principle of the student-choice construct is that choices are made in "situated" contexts. This refers to students' values, beliefs, and external factors such as financial means and financial incentives. Each student makes his or her decision based on his or her own aspirations, preferences, beliefs, desires, and resources. Thus, low-income students may make different educational choices than higher-income students due to their financial constraints even if other conditions such as academic achievement and aspiration are equal or similar. For example, students' choice of college could be influenced by family background such as parents' occupation and aspirations, students' aspirations, academic achievement, labor market changes, and expected earnings. The notion that students make choices in situated contexts is consistent with the theory of rational choice, where personal preferences and external as well as internal constraints are seen to play vital roles in rational actions.

As discussed in the first chapter, college student decision making is a dynamic interaction between the higher education system and students who are defined by their personal traits and contexts. The two principles of the student-choice construct represent such interaction. As applied in research that has explored the mechanism of student decision making (Paulsen & St. John, 2002), the student-choice construct by St. John et al. (2001) examines student choice primarily from the perspective of the relationship between student choice/outcome and the effects of public policy such as financial aid policy, rather than from the perspective of students' characteristics. From the former perspective, the choice of college major is examined by looking at the relationship between debt and major choice, and the importance of major choice mainly lies in the linkage between human resource planning and higher education finance. However, the authors recognize that a significant link between debt and major choice has not been established by empirical evidence. Thus, it is necessary to examine the student decision making process through some other perspective. St. John et al. emphasize that the role of financing policy should be examined within students' individual contexts, indicating that personal constraints may be a viable perspective in the investigation of student decision making, including college major choice. While the student-choice construct mainly focuses on how student choice and educational attainment can be promoted through institutional, state, and federal policies, it is also important to examine whether students' financial background influences their higher education choices. Looking at the relationship between students' financial context and their major choice pattern is a step towards such goal. In fact, this is what has been suggested by the authors (St. John et al., 2001), who point out the importance to examine the choices made by diverse student groups.

**Human Capital Theory**

Rational choice theory emphasizes the relativeness of rationality for different individuals, which is related to individuals' preferences, beliefs, desires, as well as personal and environmental constraints. While Holland's career choice theory focuses on psychological aspects of the decision making process and explains how personal preferences influence the choice of study field and career, social and economic factors that represent personal and environmental constraints remain to be explained. Researchers widely agree that that postsecondary education and career decisions are affected by external constraints. As Bucher (1979) points out, pervasive social constraints consist of a person's characteristics including one's gender, age, ethnicity, family composition, and socioeconomic status. These characteristics determine one's position in society, which helps formulate one's perspective on the world. A person's position in society and perspective in turn will also influence his or her social horizons. In regard to career decision making, this means that the visibility of occupations is likely to vary for people with different social positions and perspectives. This suggests that personal preferences and competencies are not the only determinants of decision making. Social constraints may also affect people's understanding of educational and career options. Dresch (1979) argues that socioeconomic characteristics and personal experiences may influence people's subjective perceptions of the labor market and educational opportunities. As a result, individual subjective perceptions may not reflect changing realities, resulting in uninformed decisions.

The vital role played by environmental constraints on education goes beyond the influence on decision making. Hossler, Schmit, and Vesper (1999) argue that social and economic factors continue to exert influences on students even after they have finished their formal education. Attending college brings benefits that last for people's life time. College education leads to increased human capital (DeYoung, 1989), higher income, increased career mobility, and better life quality (Pascarella & Terenzini, 1991). On average, college graduates have advantages over those who lack college education. The return of college education to individuals depends heavily on factors such as students' family background, demographic characteristics, and the characteristics of the college one attends. Students from lower classes and/or disadvantaged gender/race/ethnicity groups tend to benefit less from college than their peers from higher social classes (Anderson & Hearn, 1992).

Family income is one of the most important factors in students' educational decision making. After high school, students from low-income families start full time work more frequently than those from high-income families. Students from low-income families who go to college tend to attend vocational schools, technical schools, and two-year institutions (Hossler et al., 1999) more frequently than four year schools. Although family income is not statistically related to the formation of students' aspiration for college education, it does play an important role in students' realization of their college education aspiration (Hossler et al., 1999). Parents' education level strongly influences students' college aspirations and the realization of such aspiration, favoring students whose parents have higher education level (Hossler et al., 1999).

The influence of social class on educational outcome and vocational choice is also widely recognized (Osipow & Fitzgerald, 1996). Although formal schooling has been an important channel of social class mobility, students tend to follow educational trajectories not too different from their parents' social classes and hence making the social mobility rates relatively low (Van de Werfhorst, 2002). This means that students from various social class backgrounds tend to remain close to their social origin (Mullen, 2010). Research has shown that students' college major choice appears to be related to their social class background (Goyette & Mullen, 2006). Privileged students prefer more prestigious study fields including arts, humanities, mathematics, and social and natural sciences while less privileged students prefer less prestigious, applied fields of study (Sanderson, 1993).

All of these influences of environmental constraints point to the necessity of examining college student decision making from sociological and economic perspectives (Unruh, 1979). While the former focuses on influences of culture, community, school, and family, the latter emphasizes the demand for higher education from the human capital perspective. The main argument of human capital theory is that the education students receive instills skills and knowledge in them and raise their productivity, which brings financial and other rewards (Becker, 1992). In this sense, formal education, including higher education, is an investment for students. If higher education generates additional income in the future, investment in it is considered a good one from the perspective of human capital theory.

As a central issue of neoclassical growth theory, the notion of human capital has been a theoretical and empirical focus of economics since the 1960s (Langelett, 2002).

The basic framework of human capital theory is investment-output. The qualities of individuals that increase the productivity of the work force are referred to as human capital. Like other forms of capitals, it is argued that investment can be made to human capital as well, which will bring future returns (Langelett, 2002). It is believed that human capital is an important source of economic growth.

The notion of human capital can be traced back to the rebuilding of Europe after World War II, when West Germany achieved tremendous economic growth in a short period of time. Economists began to argue that one of the most important factors that promoted such remarkable economic development was human capital. The idea that both private and public sections would benefit from investment in human capital further enhanced people's interest in the newly formed theory of human capital. It has long been argued that adequate health and nutrition are important aspects of a strong work force. After the notion of human capital captured people's attention, work related qualities and skills became the focus when evaluating the productivity of a work force. Soon, economists began to link formal schooling with increase of human capital and economic development. According to human capital theory, the accumulation of human capital takes place in human beings in the form of acquisition of knowledge and skills. People began to be viewed as a type of resource, similar to physical resources such as building materials and monetary capital (DeYoung, 1989). Economists began to advocate for expanded education for people of various age groups, hoping to build a stronger work force for the economy.

Since human capital consists of intrinsic qualities of individuals, the investment in this type of capital differs from that in physical capital. Education, including formal schooling and short-term trainings, is considered to be the primary source of increase of human capital. Since the investment in human capital is made directly with each individual, it is argued that people have certain control over how much and what type of human capital investment they receive. In other words, people make decisions about education, career, and other issues related to human capital investment and future returns.

An important assumption of human capital theory is that people are rational actors in their decision making about economic issues. As discussed earlier, rational behavior refers to the action of calculating and comparing the cost and expected returns before making decisions. Assuming that people act rationally when they make decisions about human capital investment in the form of higher education they receive, opportunity cost related to higher education and expected future benefits are weighed (Langelett, 2002). The possible balance between cost and return serves as part of the rationale behind the decision. Opportunity cost consists of the amount paid for the education and the income foregone because of spending time to receive education rather than to work. Expected future benefits include financial, social, and health benefits, among others.

Individuals' calculation of costs and expected benefits are mainly based on private returns. Researchers have raised questions about the mechanism of rational choice in regard to human capital investment decision making. One of the major questions is concerned about the reasons why people choose to limit the level of investment in their own human capital to a certain level rather than to maximize it, given the fact that the aggregated return to human capital investment exceed the explicit costs

(Langelett, 2002). While some cite the lack of information about education, its cost, and its potential financial benefits for individuals to be the reason of why some people do not seek further investment in their own human capital (DeYoung, 1989), a more fundamental reason of why investment in human capital does not take place with many people is financial constraint, especially on the individual's part. Individuals either have no funds for education, or cannot afford education because the opportunity cost is too high (Langelett, 2002). It is argued that to encourage individuals to make investment in their own human capital, efforts to influence the costs and/or the benefits of such investment should be made. While it is difficult or even impossible to influence the benefits of human capital investment, lowering the cost of education is a viable way to influence people's decisions regarding the investment they make in themselves (Langelett, 2002).

For students facing choices regarding higher education, lower cost means better chance of increased investment in their human capital and higher expected future income. While students have no influence on the cost of obtaining higher education, all they can do is to choose an educational path that they can afford financially while trying to increase the human capital investment in themselves. According to human capital theory, it can be assumed that the necessity to obtain balance between cost and investment influences how students make decisions.

Human capital theory has been widely adopted in educational research as theoretical framework. Perna (2005) applies the theory in the examination of the differences in benefits of higher education for diverse student groups. The economic perspective of human capital theory has been adopted to examine whether debt from undergraduate study influences STEM students' enrollment in graduate school (Eagan & Newman, 2010; Malcom & Dowd, 2012). Findings suggest that the theory is explanatory of students' decisions regarding graduate school enrollment. Tannen's (1978) study findings show that although higher education decisions are made in a relatively early stage of people's life, the pattern of such decisions appears to be rational economic as indicated by human capital theory. Expected higher income in the future is proven to influence students' decisions of college attendance (McMahon & Wagner, 1981; Willis & Rosen, 1979), providing support for the principle of human capital theory that suggests that individuals weigh the costs and benefits before deciding the level and type of human capital investment in themselves. Solmon's (1981) study shows that the decision to attend college is a wise one for most people, a point that is widely recognized and followed by students.

The assumptions of human capital theory are supported by empirical evidence, too. Manski and Wise (1983) examine academic, SES background, labor market conditions, and demographics factors to predict student college enrollment probabilities. Research suggests that other factors being equal, students prefer less expensive institutions. Moreover, findings suggest that the higher the expected foregone income, the lower the probability of college attendance (Manski & Wise, 1983), providing evidence that economic considerations do play a role in students' college attendance decision making.

Evidence from these studies suggests that human capital theory is explanatory in examining college students' decision making. Interestingly, one area that has largely eluded the framework of human capital theory is how students make decision about their college major.  Although research has shown that the choice of major plays a deciding role in students' efforts to maximize the utility of college education (Solmon, 1981), the pattern of decision making in this regard has not been investigated from the economic perspective of human capital and rational choice theories frequently.  As St. John et al. (2001) point out in their discussion of the student choice sequence, college major choice is no less important than other decisions such as college attendance or persistence.  Given the role college major plays in the differential expected financial rewards (Rumberger, 1984; Rampell, 2011), it is plausible that an economic perspective rooted in human capital theory and rational behavior explains students' decision making pattern in terms of study fields.

## STEM Education in College

During the past several decades, the promotion of STEM education in both k-12 and postsecondary levels has been a focus of nationwide educational discussion.  The issue originates from concerns about the shortage of qualified STEM work force that is necessary for the economic growth.  Researchers, educators, and policy makers have tried to understand how to increase students' interests in STEM fields, help them persist for degrees and eventually, opt for STEM careers.  Similar to the college student choice sequence (St. John et al., 2001), students' decisions regarding STEM majors consists of the formation of interests and aspirations for STEM education and career, the choice to enroll in STEM majors, the choice about whether to persist in STEM majors, the decision regarding whether to pursue graduate education in STEM fields, and finally the decision of whether to pursue a STEM career.

**The Choice of College Major**

Besides the decision of college attendance and choice of college, the choice of college major is one of the most important higher education decisions that influence students' development trajectory and career opportunity. The choice of major plays a crucial role in students' future earnings, graduate education opportunities, and career trajectories (Mullen, 2010). It gives students chance to learn the subjects that interest them, to develop their intellectual potentials, and it is directly linked to college persistence (Arcidiacono, 2004; St. John, Hu, Simmons, Carter, & Weber, 2004). For example, differential major distribution between male and female has been shown to contribute to gender wage gap for college graduates (Angle & Wissmann, 1981; Eide, 1994), and graduates with degrees in economics tend to earn more than other majors (Black, Sanders, & Taylor, 2003). In this sense, the choice of college major is a source of class inequalities. Students' choice of major, although appearing to be a discretional decision, not only reflects the existing class division, but also forms new class division among students and within higher education. Since the choice of college major both reflects one's social, cultural, economic, and educational background and decides one's future educational, social, and economic development, it can either help to maintain the status quo or serve to break it. In other words, the social, cultural, and economic stratifications among student groups can either be reinforced or gradually broken, depending on the pattern of how students self-select into different study fields and career paths.

The choice of major not only influences students' career trajectory, it is also an important dimension of higher education stratification. While the hierarchy of differentiation in institutional prestige forms an external stratification in higher education, varying power and prestige attached to major fields also form an internal stratification of no less significance (Braxton & Hargens, 1996; Thomas, 1985). Much of the power difference among study fields stems from their perspective economic return, making college majors like engineering and business more prestigious and desirable (Davies & Guppy, 1997; Rumberger & Thomas, 1993). Thus, the choice of college major is recognized as an important educational decision, both as an outcome of accumulative educational experiences and as a determinant of future educational and career outcomes (Turner & Bowen, 1999).

Choosing a study field in college appears to be a decision made by students based solely on their free will. In fact, numerous factors influence how students make this decision and to various extents, narrow the choice for different student groups. Several factors are associated with students' major decision, including high school achievement (St. John, 1994b), self-assessment of major field competence (Correll, 2001; Trusty & Ng, 2000), high school experiences, ability, and taste (Federman, 2007), parental encouragement (Pearson, 1997), family income (Staniec, 2004), influences of role models (Hackett, 1989; Rask & Bailey, 2002), expectations of the outcome (Lent, Lopez, & Bieschke, 1993), and perception of the profession (Cohen & Hanno, 1993; Worthington & Higgs, 2003).

Educators and policy makers are concerned with how to promote the enrollment in certain academic fields, such as STEM fields. Research shows that students' college experiences, such as perceptions of the first courses they take in a certain field (Geiger & Ogilby, 2000), impacts subsequent choice of major. Considerations of option value such as the probability of graduate school attendance also influence students' decision

(Eide & Waehrer, 1998). Expected future earnings impact the choice of major, suggesting that students tend to follow the economic principle of rational behavior when they decide which study field to choose (Arcidiacono et al., 2012; Berger, 1988; Cebula & Lopes, 1982; Easterlin, 1995; Malgwi, Howe, & Burnaby, 2005).

**Research on STEM Education in College**

Because of the critical role of STEM fields in the economic growth, much attention has been paid to the STEM education pipeline. Research shows that various factors may influence college major choice in STEM fields. STEM majors' demanding requirements have led researchers to focus on the influence of academic factors on STEM enrollment. Pre-college academic preparation has been cited as one important factor that influences students' decision on STEM enrollment (Rask, 2010). High school course-taking, especially in math and science subjects, (Ethington & Wolfle, 1988; Li, Alfeld, Kennedy, & Putallaz, 2009; Trusty, 2002; Tyson, Lee, Borman, Hanson, 2007; Young, 2005), high school academic achievement and SAT score (Crisp, Nora, & Taggart, 2009; Smyth & McArdle, 2004; Turner & Bowen, 1999), math self-efficacy (Betz & Hackett, 1983; Hackett, 1985), and overall academic ability (Nicholls, Wolfe, Besterfield-Sacre, Shuman, & Larpkiattaworn, 2007) are cited most frequently for their positive correlation with college students' STEM enrollment. Besides pre-college preparation, student personality, student political view, and family influence have also been examined and are reported to have different levels of relation to college major choice in STEM fields (Porter & Umbach, 2006; Smith & Hausafus, 1998; Smyth & McArdle, 2004). Cultural factors also play important role in students' decision making. Xie and Goyette (2003) argue that Asian American students tend to select study fields of technical and science nature partly due to their lack of cultural capital, which is important for success in many other academic fields.

How to prevent STEM pipeline leak in college has also received much attention from researchers. Price (2010) finds that black faculty members serve as role models and increase black students' likelihood of persisting in STEM majors, while the number of female faculty members is negatively related to female students' persistence in STEM fields. Female students' college experiences, such as connection with peers and participation in research programs, increase their persistence in STEM fields, while enrolling in highly selective institutions decreases the possibility of female students persisting in STEM majors (Espinosa, 2009).

Seymour and Hewitt (1997) discuss the mechanisms behind students' decision to leave science, mathematics, and engineering (SME) majors in college thoroughly. They suggest that materialism and pragmatism are recurring reasons why students decide to enter SME majors. Whether the notion comes from parents, friends, community, or the public media, some students choose SME majors for the prospected high economic return and occupational prestige. Some students of color express the wish to make financial contribution to their family or community and cite this as a reason of why they choose SME major.

However, Seymour and Hewitt (1997) also find that later in students' college career, pragmatic considerations in major choice will not hold as strong as reasons such as intrinsic interest in certain discipline. Low-income students tend to give up SME major after sometime due to the conflict between the financial burden they carry and the demanding workload of SME majors. Low-income students, whether white or minority, find it difficult to work to make financial needs met while at the same time maintain satisfactory grades in SME majors. Although these findings suggest that entering an SME major does not mean success in that major, they do not discount the observation that some students do take future economic return and occupational prestige into consideration when they make decision of what major to choose in college. Given these findings, it is worth exploring whether family SES and choice of STEM major is systematically associated. If the findings show that low-SES students tend to prefer STEM majors, policy makers should design more ways to help such students focus on study rather than being distracted by financial concerns.

Seymour and Hewitt's (1997) work discusses students' college career in SME majors and why some switch to non-SME majors while others persist. While such discussion is highly insightful, the study focuses mainly on what happens after students have self-selected into SEM majors. How and why students have entered these majors in the first place has not been thoroughly explored. The qualitative approach adopted in their study reveals some reasons that impact students' decision regarding SME majors. Although the work is highly informative and insightful, the nature of qualitative method limits the conclusions of the study to the sample; the conclusions are not generalizable to the broader student population.

Most studies investigating the enrollment and persistence in STEM majors in college are conducted from the perspectives of gender and/or race/ethnicity gap. Gender gap in enrollment exists in certain academic fields, such as economics and STEM fields (Dynan & Rouse, 1997). The enrollment gap between male and female leads to income gap after graduation (Daymont & Andrisani, 1984). The gender gap perspective examines the role socialized gender identity plays in students' college major and career decision making (for example, Dickson, 2010; Maple & Stage, 1991; Riegle-Crumb & King, 2010). Explanations of the underrepresentation of female students in STEM fields include social forces, gender roles, negative perception of STEM professions, and different levels of sensitivity to grades (Eccles & Jacobs, 1986; Frehill, 1997; Rask & Tiefenthaler, 2008). Female faculty members act as role models for female students and influence their major choice in male-dominated academic fields such as engineering and economics (Ashworth & Evans, 2001; Qian & Zafar, 2009).

Racial/ethnic enrollment difference is another common perspective adopted in research in college STEM education. Such focus stems from the racial/ethnic gap in terms of STEM achievement. For example, the influence of college major field on students' persistence differs by race (St. John et al., 2004). While it is generally agreed that racial/ethnic differences in STEM enrollment and achievement exist, findings regarding specific differences are relatively inconsistent. Simpson (2001) examines college major enrollment pattern by examining the different associations between determinants of college major choice across racial groups and finds that both the major enrollment pattern and the influence of determinants mainly only differ for Asian Americans and non-Asians. Kelly (2009), on the other hand, finds that there is gap in mathematics course taking between African American and white students. Except for Asian students, who are found to prefer STEM and other quantitative study fields over humanities and social sciences (Xie & Goyette, 2003), research has not found specific major choice patterns for other racial/ethnic groups. Most examination of factors influencing disparities in STEM major choice has focused on predictors that are common to all groups, such as academic preparation.

Organizing the investigation of STEM enrollment along the gender and racial/ethnic dimensions results in findings pertaining to one gender or racial/ethnic group with limited generalizability across the entire college student population. For example, Crisp, Nora, and Taggart (2009) examine the impact of demographic, pre-college, personal life, and college factors on students' choice of and persistence in STEM fields, focusing on Hispanic students enrolled at a Hispanic Serving Institution (HSI). The authors examine the differences between Hispanic and white students and Hispanic and white STEM field majors at an HSI and explore predictors of choosing, switching to, and persisting in STEM majors. Demographic characteristics, educational factors, and college experiences are examined as potential predictors. Findings suggest that differences exist between Hispanic and white STEM majors in terms of first-generation status, enrollment status, financial support, and SAT score, with Hispanic students in disadvantaged status. Consistent with previous research findings, demographic characteristics and pre-college factors are found to be associated with choosing STEM majors. The authors conclude that HSIs could be an important access point for Hispanic students to succeed in STEM fields because based on the sample data, being Hispanic is related to higher likelihood of initial choice of STEM majors. While the conclusion may shed light on STEM enrollment of Hispanic students at the Hispanic Serving Institution where data are collected, the generalizability of the findings is limited due to the unrepresentativeness of the sample. Moreover, the findings apply to only one racial group and thus do not contribute much to the understanding of the general student population. Common to studies focusing on one racial/ethnic group, the data availability of this study is limited, making it impossible to include more important potential predictors in the model. As the authors point out, factors such as attitude and preferences for certain major fields, which are yet to be included in the model, could reveal a more complete picture of which students are entering which major fields in college.

While scholarly work accumulates to understand how to encourage women and underrepresented minority students to choose STEM majors in college and how to increase persistence in these fields, less attention has been given to the whole student population's general enrollment pattern in STEM fields. Compared to the aforementioned factors, more fundamental factors such as students' social and economic background that may influence educational outcome, have received less attention. Researchers have argued that students' family socioeconomic status is a strong predictor of educational outcome in general and is connected to students' educational aspiration, schooling track, academic achievement, persistence, and career choice (Schreiber, 2002). However, the effect of SES on college major choice in STEM fields has not been well examined. Although the aforementioned studies reveal the plausible correlation between family SES and college major choice, none has focused on major choice in STEM fields. Studies that have focused on students' decision about STEM majors have largely neglected the perspective of family SES and economic return of college education. In other words, although it is clear that factors such as academic preparation and aspiration predict the enrollment in STEM majors, less is known about whether the enrollment pattern in STEM fields is systematically associated with students' characteristics related to socioeconomic background.

## Socioeconomic Status and College Education

The association between family SES and educational outcome has long been shown by research. Students' learning opportunities are stratified well before college, both between schools and within schools (Gamoran, 1987). Students from low SES background often suffer from the lack of experienced teachers, low expectations, and insufficient school resources (Flores, 2007). The tracking system in secondary education often makes it difficult for students from low SES background to take advantage of the educational opportunities that college offers. For example, students who are not able to enroll in advanced math and science courses in high school are less likely to be able to choose college majors that are intense in quantitative knowledge. The influence of family SES on students' academic achievement is not only reflected in the unequal distribution of learning opportunities in schools, but also reflected in the interaction modes of parents and children in family, which differ by family SES (Davis-Kean, 2005). For example, parents from low SES families tend to base their expectations for their children's education on their recall of children's previous performance. However, since such recall is frequently erroneous, parents' expectations tend to negatively affect their children's academic achievement (Alexander, Entwisle, & Bedinger, 1994). The influence of family SES on students' academic achievement is also reflected in the availability of educational resources at home, which is inevitably affected by parents' financial and cultural resources (Teachman, 1987). Even when controlling for factors such as home environment, family SES still plays a significant role in predicting students' academic achievement, suggesting the prevailing influence of

SES on educational outcome (Crane, 1996). Family SES also explains some of the disparities in the academic achievement between different racial groups. Watson (2012) finds that after controlling for family SES factors, the achievement gap between black and white students diminishes to a statistically non-significant level.

Family SES does not only affect how well students perform in schools, but also affects the level and type of education they receive. The disadvantaged position of low-income students in higher education in general leads to the question of whether family socioeconomic status influences students' enrollment and success in STEM fields, controlling for other predictors such as academic preparation.

**Low-Income Students in Higher Education**

Low-income students are disadvantaged in terms of opportunities for college education. Compared to the underrepresentation of minorities at elite institutions, the underrepresentation of low-income students is many times greater (Kahlenberg, 2004). In the 1960s, students from high-income families were five times more likely to attend college than their low-income peers (Gladieux, 2004). The affordability of higher education for students from low-income families has decreased over the past decades. The steep rise of college tuition, the widening income gap, and the changes in financial aid policy which disfavor low-income students have contributed to college becoming increasingly unaffordable for students from the low end of the economic scale. Starting the 1980s, college tuition soared at a pace twice or more the consumer price index (CPI) (Gladieux, 2004). From 1980 to 2000, the median family income rose 27%, while the average, inflation-adjusted tuition more than doubled at four-year institutions (Gladieux, 2004). Also, the gap between different family income groups has been widening. The result is that the cost of college as a share of family income has increased the most for low-income families. The net college costs as a percent of median family income have risen from 39% in 1999-2000 to 55% in 2007-2008 for families of the lowest income quintile (The National Center for Public Policy and Higher Education, 2008). Since 2000, the percentage of family income after financial aid needed to pay for a public four-year institution has increased in all states but two. The average percentage of family income needed for such a college education for students from low-income, middle-income, and high-income families are 40%, 25%, and 13%, respectively (The National Center for Public Policy and Higher Education, 2008).

Although low-income students now need more financial support to gain access to higher education than ever, the federal and state financial aid policies have gradually shifted away from the need-based principle of programs such as Pell Grants. On the federal level, financial aid policy has shifted from grants for the poor to loans that put the burden on students and their families. As a result, low-income students may be less inclined to enroll in college due to concerns about indebtedness. On the state level, merit-based, need-blind financial aid programs, such as the Florida Bright Futures Scholarship program, have gained huge popularity among parents and students. These programs steer public funding to students with high academic achievements regardless whether they are in need of financial support to attend college. Inevitably, low-income students are less competitive in receiving such financial aid.

As discussed in the first chapter, social stratification in the United States is related to gender, race, and class. While gender and race have received much attention in both public discussion and scholarly research of educational equity and access, for example in STEM education, class and socioeconomic context/status have been frequently ignored in efforts to explain college access issues (Mixon, 2007). The underrepresentation of low-income students in higher education is greater than that of racial minorities (Carnevale & Rose, 2004). The public finds it a greater disadvantage to be from a low-income family than to be a racial minority. At the most selective institutions, socioeconomic diversity is even smaller than racial or ethnic diversity (Carnevale & Rose, 2004). While racial affirmative action has benefited minority students, the lack of economic affirmative action makes it difficult for students from low socioeconomic background to gain access to higher education, especially at selective institutions. The underrepresentation of low SES students in highly selective institutions denies them equal opportunity both in higher education and in future development and benefits.

In the United States, students are segregated by socioeconomic status through residential patterns. People of higher socioeconomic status tend to live in neighborhoods with quality schools, while those of low SES tend to live in communities where schools are not properly funded. Students of different SES go to schools of different quality, which leads to different levels of academic preparation. When low SES students have access to high quality high schools, they achieve higher academically than their low SES peers who attend low quality high schools and more frequently enroll in selective higher education institutions (Carnevale & Rose, 2004). Although students from low SES background have the most to gain from attending college, they appear to benefit the least from higher education (Anderson & Hearn, 1992). In general, low SES students tend to enroll in lower-quality tertiary institutions, attend college part-time, and are less likely to persist or attend graduate school (Manski & Wise, 1983; Terenzini, Cabrera, & Bernal, 2001).

**SES and College Decision Making**

There is little doubt that SES influences educational, occupational, and income attainment. Two types of stratification exist in higher education, the intra-institution hierarchy of institutional selectivity and the inter-institution hierarchy of fields of study (Davies & Guppy, 1997). The various prestige and power associated with the stratification lead to different educational and career outcomes. The existing social class structure reproduces itself through students' college and major choices, which are influenced heavily by the socioeconomic status they bring into college.

Family SES not only influences how students attend college and what they achieve, it also has strong impact on why students attend college and what they aim to gain from college education. Financial consideration is a primary factor that distinguishes students from different SES background in this respect. Students from different SES families have different considerations about financial issues of their college education. Those from high SES families know that their parents will pay for their college education, while those from low SES families often find financial burdens to be mostly their own responsibility. Some low SES students choose major based on their experience of high school jobs and parents' knowledge about the labor market and occupation structure. For parents from low SES families, they recommend that their children pursue a good job with a decent salary. However, due to the limit of the parents' own horizon on occupations, students from low SES families oftentimes make choices based on very limited information (McDonough, 1997).

For low-income students, higher education's economic value is one of the foremost reasons of college attendance (Corrigan, 2003). Low-income students more frequently see higher education as occupational training and attend college for preparation to enter the workforce (Lee, 2002). In times of economic downturn, non-traditional low-income students tend to turn to college for a gateway to better financial stability. Because they aim to realize the economic benefits of higher education through academic success and program completion, they disproportionately enroll in shorter-term, lower-priced programs hoping to begin to receive economic rewards as soon as possible (Lee, 2002).

High SES students more frequently expect to go to graduate school, and do not care too much about their specific undergraduate major in terms of marketability. To the contrary, student of lower SES tend to choose college major based on occupation goals rather than on personal interest or the pursuit of knowledge itself. For these students, college major means occupational preparation rather than academic discipline or domain of knowledge. The class-based pattern of major choice holds both across and within institutions. Even within highly selective institutions where most majors are liberal arts majors, students from lower SES background are still more concerned about the applicability of their major on the labor market than their peers from higher SES background (Mullen, 2010). In other words, less privileged students face the necessity of majoring in a field so that the knowledge and skill they acquire through college education are practical and marketable, suggesting that low-income students are constrained by economic factors when making higher education decisions.

Empirical evidence supports the influence of family SES on students' college decisions and career trajectories. Sianou-Kyrgiou (2010) finds that college students' choice of study field is systematically influenced by their family socioeconomic status as represented by their fathers' educational level and social class. The author concludes that college decisions are "made within a certain context that is, to a great extent, socially pre-defined" (Sianou-Kyrgiou, 2010, p. 35). Van de Werfhorst (2002) finds that social mobility through higher education is relatively low due to the fact that college students' choice of study field is confined by their family socioeconomic status, which to some extent reinforces their social origin. The influence of socioeconomic background factors in students' choice of college is significant even after controlling for educational factors (Hearn, 1984), and lasts even after students finish the highest degree in their fields and start their careers.

The investigation of the association between family SES and student decision making has been guided by various theoretical frameworks. Simpson (2001) argues that if students choose college majors according to the principles of status attainment theory, (which suggests that the social relations of education correspond to the social relations of the larger society), students from low SES background would follow the paths of their parents and tend to choose college majors that are less lucrative. However, this assumption is not supported by empirical findings, suggesting that status attainment theory does not explain well how students' decision making is confined by their social background. More studies adopt the economic perspective, which focuses on the role played by financial factors and assumes that students are rational actors in making college related decisions. Ma's (2009) study suggests that students of lower

SES tend to choose “technical, life/health science, and business majors — those higher paying fields upon graduation — over humanities and social science/education majors” (p. 227).

Goyette and Mullen (2006) examine the effect of social background on college major choice and the consequences of choosing different college majors, focusing on the contrast of liberal arts education and early career training. Results show that students of low SES are more likely to choose vocational majors, while those of higher SES are more inclined to major in arts and sciences. Following graduation, students of vocational majors are more likely to seek full-time employment, while students of arts and sciences majors are more likely to enroll in graduate school. These results imply that students of lower SES are more inclined to seek economic return soon upon college graduation, while student of higher SES could afford to postpone economic return by extending higher education to graduate school. The finding that when choosing college major, low SES students value immediate economic return more than their affluent peers suggests that SES is systematically related to students’ choice of study field and career trajectory.

Davies and Guppy’s (1997) study examines whether students’ race, gender, and SES directly and indirectly affect students’ enrollment at selective institutions, in lucrative major fields, and in lucrative major fields at selective institutions. Their study investigates whether students’ social background has lingering effects in postsecondary education by influencing students’ choice of institution and major field. Findings suggest that higher SES and more cultural resources are positively related with enrolling in selective institutions and lucrative majors at selective institutions, though the effect of SES is largely indirect through academic achievements. Controlling for academic achievement factors, students of low SES tend to enroll in lucrative fields of technical nature, “such as engineering and business” (p. 1427). Contrary to what the authors expect, students from high SES background are actually less likely to enter lucrative major fields. SES and academic ability strengthen each other’s effect on enrollment at selective institutions. These findings support the notion that students from different SES background have different financial considerations, which constrain their decision of study field. The authors conclude that based on the aforementioned findings, social background continues to influence students after they complete high school and enter college. This would influence both institutions and students. For institutions, vertical and horizontal stratification through unequal opportunities of access for students of different social backgrounds results in further self-perpetuation and more uneven allocation of resources among fields and institutions. For students, lingering effects of social background on college and major choice further affects the educational opportunities of disadvantaged students. Increased stratification in higher education would inevitably result.

Leppel, Williams, and Waldauer’s (2001) study examines college students’ major choice through the perspective of SES, specifically, through the impact of parental occupation as a proxy of SES. The authors hypothesize that parental occupation influences students’ major choice and mother’s occupation would have more influence, especially for daughters. They further hypothesize that students’ family SES and attitude towards financial wellbeing would both influence major choice, though the impact of family SES would be larger for women than for men. Findings suggest that parental occupation impacts students' major choice; but this impact does not differ for mother and father. Students' attitude toward financial wellbeing does influence students' major choice in that students who find financial wellbeing to be very important are more likely to choose business majors than other major fields. Family SES has influence on major choice in that when SES increases, both male and female are more likely to choose humanities and social sciences over health majors. Similar to Davies and Guppy (1997), Leppel et al. (2001) also conclude that the influence of family SES background on college major choice leads to within-institution stratification in higher education.

## Conceptual Model for this Study

In the previous sections, I have discussed the higher education literature on college student decision making, STEM pipeline in college, and the association between SES and college decision making. In this section, I summarize the current literature, describe the conceptual model used in this study, and discuss the theoretical hypotheses to be tested.

### Research Direction Pointed by Current Research

The process of decision making by college students is complex yet important. Understanding how and why students choose various educational paths is a key to effectively promoting diversity in higher education. Understanding the mechanism of this process requires careful examination of students' social, cultural, and educational contexts. Scholarly efforts to address this issue have mainly followed two lines of theoretical framework. The first focuses on the psychological aspects of the decision making process, emphasizing the importance of individuals' preferences, beliefs, and competencies. Holland's vocational choice theory argues that students make educational and vocational decisions based on their personality type. Students evaluate the educational or vocational environments and choose one that is the most congruent with their personality. The goal is to choose an environment that rewards one's skills, competencies, and preferred activities. In other words, personal preferences and interests play deciding role in students' decision making process.

While the psychological explanation of student decision making captures the interaction between personal preferences and environmental characteristics, it is worth asking whether this is the major deciding factor for all students. As discussed earlier, the changing higher education system has been posing new challenges, especially for underrepresented students. In a time when access and equity in higher education are yet to be achieved, making decisions based on personal interests and preferences might in fact be unaffordable for some students. Factors other than personal preferences might be more pressing and weigh heavier in students' considerations of their educational choices. Human capital theory and rational choice theory provide a framework to examine such factors from an economic perspective. Assuming that individuals act rationally by calculating the costs and expected benefits before deciding on what action to take, human capital theory argues that higher education is an important form of investment in people's productivity related skills and competencies. Increased investment in human capital is expected to bring increased financial rewards in the future. Rooted in economics, human capital theory and rational choice theory provide a framework for examining how financial factors influence people's decision making. Given that the average financial rewards of college education do exceed the incurred costs, the question remains to be answered is why individuals choose different investment levels in their own human capital. According to rational choice theory, costs or benefits alone do not decide people's choices. Rather, it is the balance between the two that plays a significant role. In the case of choosing educational path, this means the dynamic between the expected financial rewards of college education and the incurred costs contributes much to students' decisions. Based on rational choice theory, the notion that students make decisions within contextual constraints recognizes the complexity of students' reality. Such reality goes beyond personal preferences and places students within layers of factors that might have bearing on their educational choice.

Within the sequence of decisions that college students make, choosing college major is important because it influences students' educational and career trajectories in numerous ways. It reflects students' prior educational experiences, and decides their future development paths. In this sense, choosing college major reflects students' social background and forms a new social structure that to some extent reinforces the existing one. STEM education has been frequently examined because of the significant role it plays in the economic growth and also because of the lack of diversity in STEM fields. Due to the demanding academic standards of STEM majors, researchers have more frequently focused on academic factors as predictors of STEM enrollment. In terms of social factors, most studies investigating access and equity in STEM areas have adopted the perspective of gender and/or race/ethnicity gap. Despite the fact that social class also forms an important dimension of inequality in higher education, less attention has been paid to how college students' social background is related to their enrollment in STEM fields.

That family SES influences educational outcome in numerous ways, both directly and indirectly, is widely recognized. Low-income students are underrepresented in the higher education system in terms of quantity as well as quality. Financial barriers, for example, reduce their access to higher education. Academic preparation level, financial considerations, occupational perspective, and influence from family and community all contribute to students' choices regarding college education. Students from low-SES families tend to view college education primarily as training for the job, while those from high-SES background tend to see college education as a way to pursue knowledge for its own sake. Although previous research findings have suggested that students' choice of study field is related to their family SES, the economic perspective of student decision making has rarely been adopted in the investigation of STEM enrollment in college. As discussed above, research suggests a correlation between family SES and college choice pattern through students' pursuit of different types of reward. Given STEM majors' strong advantage in economic return (Langdon, McKittrick, Beede, Khan, & Doms, 2011), it is worth exploring the enrollment pattern along the dimension of family SES.

**Conceptual Model of This Study**

The research on students' college choice decision making has mainly followed three approaches, namely social psychological, sociological status attainment, and economic approaches. The social psychological approach focuses on the influence of the environment and the person-environment fit. The sociological status attainment approach focuses on the impact of students' social background on their educational aspirations and decision making. It describes how students' family conditions, environment factors such as peers and communities, and the socialization process influence their educational decision making (Hossler et al., 1999). The economic approach relies on the theory of human capital to model students' decision making as part of rational behavior influenced by financial considerations (McDonough, 1997).

Based on the review of the current literature, this study adopted the economic approach to examine college students' enrollment pattern in STEM fields. It was assumed that college students are rational actors when making educational decisions. Their educational choices are made within contextual constraints. It was also assumed that college education is a form of human capital investment in which students have certain control over the type and level of investment they make in themselves. The focus of this study was to examine the constraints imposed by students' family socioeconomic status and examine how students' decision regarding STEM majors vary with the constraints related to their family SES. Human capital theory explains how STEM majors distinguish themselves in terms of expected financial rewards. Students' family SES explains students' life reality that limits the affordability of the costs of receiving college education. The notion of rational choice combines these two parts and assumes that individuals try to achieve a dynamic between costs and expected rewards which is beneficial for them.

# CHAPTER 3
# METHODOLOGY

The objective of this chapter is to describe the methodology of this study. First, I revisit the research questions and state the proposed hypotheses based on the discussion of the current literature in the previous chapter. Next, I describe the data sources, their suitability for this study, as well as the samples used for data analyses and the merging of the datasets. Next, the dependent and independent variables included in this study are presented followed by a discussion of data analysis methods and models. The chapter concludes with a discussion of the limitations inherent to this study.

The purpose of this study was to examine college students' enrollment decision in STEM majors with a focus on students' family SES. The aim was to examine whether there is systematic association between students' family SES and their enrollment decision in STEM majors and if yes, what the direction and magnitude of the association are. Specifically, this study investigated the following research questions:

- Research question 1: Is students' family SES related to their decision of whether to enroll in a STEM major in college?
- Research question 2: Does the enrollment decision in STEM fields vary for students with different college investment levels?
- Research question 3: Does the enrollment decision in STEM fields vary at institutions with different scales and levels of STEM major offerings?

## Proposed Hypotheses

The following hypotheses were proposed:

**Hypothesis 1:** College students' family SES is negatively correlated to enrolling in STEM majors, controlling for individual, pre-college, and college factors. From the perspective of financial return of higher education for individuals, STEM majors distinguish themselves from other undergraduate majors in several ways. First, the rise of high technology and new development in sciences has become one of the strongest powers of the economic growth of the US and has largely expanded the job market for STEM graduates (Department of Labor, 2007). As a result, STEM fields in general provide better economic return through job security and higher earnings than fields such as humanities and social sciences (Rampell, 2011). Second, the time and monetary investment in STEM fields is less than those in lucrative professional education such as law and medicine (Frehill, 1997). These facts lead to the hypothesis that low SES students are more likely to enroll in STEM fields, controlling for other factors.

**Hypothesis 2:** Students' college investment level is positively related to enrolling in STEM majors. One of the goals of this study is to explore the relationship between the monetary investment students and their families make in college education and their decision of whether to enroll in STEM majors. It was hypothesized that the higher the monetary investment level, the more "precious" the college education is for students in an economic sense. Thus, students with higher monetary investment in higher education are more likely to take the economic return into consideration when they choose major.

**Hypothesis 3**: The scale and level of STEM major offerings at an institution are correlated to students' decision of STEM major enrollment. Besides familial and individual factors, students' choice of college major may also depend on the program offerings at the institution they are enrolled in. Another goal of this study was to find out whether the level and scale of STEM major offerings at an institution are related to students' decision of STEM enrollment. If a STEM program is large in scale, and/or offers graduate degrees, does it exert stronger influence on students who are seeking for a suitable major? In other words, do STEM programs' scale and quality matter in recruiting students? Based on previous research findings about the influence of institutional factors on students' decision making (Rask & Bailey, 2002), it was hypothesized that the scale and level of STEM major offerings at an institution are correlated to students' decision of STEM major enrollment.

## Data Sources

The data analyzed in this study were derived from three sources. In the following subsections, I provide a description of each data source, discuss why each of them serves the purpose of this study, and explain how the three datasets are combined for data analysis purposes.

### Education Longitudinal Study of 2002 (ELS: 2002)

The main data source of this study was the Education Longitudinal Study of 2002 (ELS: 2002) by the National Center for Education Statistics (NCES). ELS: 2002 is a longitudinal study designed to monitor the progress of a nationally representative sample of students from tenth grade through higher education and further into the workforce. The survey began collecting data with a cohort of high school sophomores in 2002. Two follow-up surveys have been conducted in 2004 and 2006. The study collects data from several respondent populations that were related to students, including parents, teachers, librarians, and school administrators. Information collected includes students' academic achievement, educational experiences, family characteristics, and school characteristics.

The ELS: 2002 follows the base year cohort of high school sophomores beyond high school, either into higher education or into the work force. Since the purpose of this study was to examine college students' enrollment decision in STEM fields, sample participants who do not attend college after high school are excluded from the analysis. Specifically, this study used these three waves of data. The base year data provided information on students' demographics, high school academic achievement, high school extracurricular activities, family socioeconomic status, parental support, and school characteristics. The first follow-up survey data provided information on students' high school course taking pattern and academic achievement. The second follow-up survey data provided information on students' college enrollment, financial conditions, and college characteristics.

**Advantage of the dataset**

This dataset was suitable for this study first because it is a nationally representative sample. Thus the results of the study will be generalizable to the national student population. Second, this dataset is both longitudinal and comprehensive. The surveys follow high school sophomores into college, providing information on students' educational trajectory. Collecting data from parents, school administrators, and transcripts provides information on students' family background, pre-college academic preparation, and college career. Information from these sources will help to control for students' family background, individual characteristics, and high school characteristics. Such information was necessary for building a comprehensive model of predicting STEM enrollment decision. Third, the ELS: 2002 dataset is the most current longitudinal dataset that collects data on students' high school and college careers. Analysis outcomes based on this dataset will reflect the most recent national trend in higher education.

### Sampling design

ELS: 2002 uses a two-stage sample selection process. First, schools are selected with probability proportionate to size. Then students are selected from the participating schools. Some subgroups, such as Hispanics and Asians, are oversampled to ensure proper sample size for analysis purposes. This means certain individuals have a higher probability of being selected than other individuals. The unequal probability of selection needs to be taken into consideration when analyzing the data collected using complex sampling designs to ensure representative and unbiased findings. Another issue that needs to be compensated for is survey nonresponse, which refers to the fact that not all selected individuals respond to the survey. Using weight is a common method to compensate for both unequal probability of selection and survey nonresponse (Lee & Forthofer, 2006). In this study, weights from the ELS: 2002 dataset were used. Specifically, the second follow-up panel weight F2F1WT was used in conjunction with cohort flag variable G10COHRT. F2F1WT is computed for all sample members who responded in the second follow-up and responded in the first follow-up, and G10COHRT is a flag indicating a member of the sophomore cohort, that is, spring 2002 10th-grader (Ingels et al., 2007).

### Integrated Postsecondary Education Data System (IPEDS): Institutional Characteristics and Completions

The second data source of this study was the Integrated Postsecondary Education Data System (IPEDS) by NCES. The IPEDS is a system of interrelated annual surveys conducted by the NCES. Institutions that participate in or apply for participation in any federal student financial aid program are required to complete this survey. Institutions report data on enrollments, program completions, graduation rates, faculty and staff, finances, institutional prices, and student financial aid. Such data provided ways to describe higher education institutions in terms of scale and level of the education they provide, and ways to analyze trends in the higher education system. Over 7,500 institutions complete the IPEDS surveys, which consist of seven areas: institutional characteristics, institutional prices, enrollment, student financial aid, degrees and certificates conferred, student persistence and success, and institutional human and fiscal resources.

**Advantage of the dataset**

For this study, the IPEDS dataset provided key information in two aspects. The first aspect relates to the second research question, which examines the relation between STEM enrollment decision and individual investment level for college education. Although the tag price of college attendance is the same for every student within an institution, the actual cost differs for individuals as a result of different enrollment status, accommodation arrangements, and financial aid. To answer this question, students' college investment level needed to be measured. However, such a measure was not readily available on the individual level in any existing dataset. The IPEDS component of Institutional Characteristics collects data regarding college costs, including tuition and fees, room and board charges, books and supplies, and other expenses. These data provided information of total price of attendance at a certain institution. The ELS: 2002 dataset provided information on students' enrollment status (in or out of state status) and living arrangements (on or off campus). Using these two sources of data, a variable of each individual's college attendance cost was created.

The second aspect refers to the third research question, which examined the relation between STEM enrollment decision and institutional STEM offerings. The

IPEDS component of Completions collects data on the number of undergraduate degrees and certificates conferred by each institution by type of program. Such data were used to measure the scale of STEM education at the undergraduate level. The type of program was categorized using the Classification of Instructional Programs (CIP) developed by the NCES, which provides a taxonomic scheme that supports the accurate tracking and reporting of fields of study.

### Data sample

The main data source of this study was the first three waves of data collected by ELS: 2002. The second wave of data were collected in spring of 2004, when students were high school seniors. The third wave of data were collected in spring of 2006, when students were college sophomores. To reflect the institutional pricing and institutional offering of STEM majors before the time students claimed college major (Spring of 2006), the 2005 data of the IPEDS were used in this study. Public use data were obtained from the NCES website in electronic form.

### Survey of Graduate Students and Postdoctorates in Science and Engineering (GSS)

The third data source of this study was the Survey of Graduate Students and Postdoctorates in Science and Engineering (GSS) by the National Science Foundation (NSF) and the National Institutes of Health (NIH). This annual survey is completed by all higher education institutions in the United States that grant research-based master's or doctoral degrees in sciences, engineering, or selected health (SEH) fields. Specifically, SEH is defined as engineering, physical sciences, earth, atmospheric, and ocean sciences, computer sciences, mathematical sciences, agricultural sciences, biological sciences, health sciences, psychology, social sciences, family and consumer sciences/human sciences, communication, neuroscience, and multidisciplinary/interdisciplinary studies (National Science Foundation, 2010).

The GSS survey collects data on the number and characteristics of graduate students, postdoctoral appointees, and doctorate-holding non-faculty researchers in SEH fields. Both individual and institutional data are collected. On the individual level, key variables include demographics, financial support sources, and type of degree. On the institutional level, collected information includes highest degree granted by GSS-eligible units, Carnegie Classification, and institutional control. The GSS is a census of all eligible U.S. higher education institutions. The most recent survey for which data are available, the 2010 GSS survey, collects data from 574 institutions. Data are reported as of the fall term of the academic year.

**Advantage of the dataset**

The purpose of using the GSS dataset was to provide proxies of institutions' STEM program level. The surveyed academic fields of the GSS dataset are not identical to the definition of STEM fields as adopted in this study (see Chapter one). As can be seen, the GSS survey includes a wider range of academic fields than STEM fields. For example, health sciences, social sciences, psychology, and communication are defined as SEH in the GSS survey. To make the data from GSS compatible with the research question, study fields not defined as STEM majors but included in the GSS survey were excluded from the dataset.

After the non-STEM major fields were excluded, the GSS data provided information of graduate education and research activities in STEM fields at the institutional level. The highest degree granted by GSS-eligible units reflects the level of STEM education. Such information reflects whether an institution is intensive in STEM fields and whether the academic influence of such fields within that institution is strong. The GSS dataset also provides information of graduate enrollment in STEM fields at institutions. The third research question of this study aimed to find out whether students' enrollment in STEM majors is related to the scale and level of STEM offerings at their institutions. Through the level of STEM education and the enrollment number on the graduate level, the GSS dataset provided proxy for answering this question.

**Data sample**

For the same reason as discussed in the previous subsection, the 2005 data of the GSS were used in this study, which were collected as of the fall semester of 2005. Public use data were obtained from the NSF website in electronic form. Since the GSS survey is a census of all eligible institutions, weighting was not applied to the data.

**Combination of Data Sources and Selection of Cases**

In order to conduct data analysis, the three data sources were combined to yield a single dataset. The IPEDS and GSS datasets, although supplemental to the ELS: 2002 dataset, provide institutional data. The combination of the three data sources was conducted by merging the three datasets using the variable of IPEDS UNITID, which is included in all three datasets. The IPEDS UNITID is a unique identification number assigned to postsecondary institutions surveyed through the IPEDS. It is also referred to as IPEDS ID. By using this variable, the three datasets were merged. Specifically, institutional variables obtained or derived from the IPEDS and GSS datasets were added to the ELS:2002 dataset.

The total sample size based on ELS was 16,200. However, only individuals with a valid dependent variable value were included in the sample for this study. Individuals with a G10COHRT value of 0 and those who enroll in an institute with no STEM major offering at the undergraduate level were excluded from the sample. This resulted in a sample of colleges that confer Bachelor's degree or higher. A total of 4,500 cases were included in the analysis data of this study. The total number of high schools sampled was 710, and the minimum and maximum student number per school was 1 and 30, respectively. The percentage of schools with only one student included in the sample is 8%. The total number of colleges was 1070, and the minimum and maximum student number per college was 1 and 50, respectively. The percentage of colleges with only one student included in the sample is 34%. Of the sampled colleges, 5% are private for-profit, 52% are private not-for-profit, and 43% are public.

## Variables

### Dependent Variable

In this study, students' decision of STEM enrollment in college was operationalized as students' choice of a STEM or non-STEM major in college. The dependent variable was a dichotomous variable indicating whether students choose a college major in STEM fields. Since such a variable was not readily available in the ELS: 2002 dataset, a dichotomous variable was created. This variable was coded with a two-digit general category based on the 2000 Classification of Instructional Programs (CIP) code frame. The sample was limited to students who have declared a college major by the time of the second wave data collection of the ELS: 2002 survey, resulting in a sample size of 4,500. For those whose college major falls into the STEM categories, the dichotomous variable was coded as 1. For those whose college major falls into the non-STEM categories, the dichotomous variable was coded as 0. As discussed in Chapter One, this study adopted the narrow definition of STEM used by NCES in its *2009 Statistics in Brief* (Chen &Weko, 2009) and defined STEM as mathematics, natural sciences (including physical sciences and biological/agricultural sciences), engineering, and computer/information sciences.  Appendix A provides a list of STEM categorization, major fields of study, and CIP majors.

**Independent Variables**

As discussed in Chapter Two, numerous factors may have influence on students' decision of college major.  Organizing potential predictors into layers was necessary to select the most important variables to be included in the data analysis.  In this study, I adopted the structure of potential predictors of college major choice developed by Crisp et al. (2009) and the conceptual model of college choice proposed by Perna (2006). According to the factor structure by Crisp et al. (2009), students are situated in a four-layer context, namely demographic background, pre-college experiences, environmental factors, and college factors.  Demographic background refers to ascribed characteristics such as gender and race/ethnicity, as well as socioeconomic status. Pre-college experiences refer to academic preparation and school experiences. Environmental factors refer to financial factors and enrollment factors that either increase or decrease students' chance of success in college.  College factors refer to students' academic achievement in college.  While this structure does include contexts of students' lives, the emphasis is placed on individual factors.  In other words, all four layers focus on how students achieve in the educational system and largely ignore the role played by exogenous factors such as school and college characteristics.

Perna's (2006) model also places students in a four-layer context.  Unlike the Crisp et al. (2009) structure, the Perna (2006) model emphasizes the fact that students' college attendance decisions are made within contextual constraints, which consist of high school context, higher education context, and social, economic, and policy context.

According to this model, the first layer is the student and family context, which refers to students' characteristics, socioeconomic background, academic preparation, and educational aspirations.  The second and the third layers are high school context and higher education context, respectively.  These two layers focus on the characteristics of schools and colleges, which may play roles in students' college attendance decision making.  The fourth layer refers to the context of the larger society, including social, economic, and policy factors.  As can be seen, this model takes into account the exogenous factors such as institutional factors in students' decision making.

In this study, I combined the two models discussed above to form a three-layer structure of student context.  The first layer was the individual layer.  This layer focused on the demographic, socioeconomic, familial, and cultural factors that define the students.  The second layer was the pre-college context layer.  This context refered to students' educational experiences before they enter college, as well as the characteristics of the educational institutions they have attended.  The third layer was the college context layer.  This layer concerned the college education context students find themselves in and students' college learning experiences.  Figure 3.1 presents the three layer structure of student context.

This three-layer structure combined the strengths of the Crisp et al. (2009) model and the Perna (2006) model.  The first layer extended the first layer of the Crisp et al. model, which only focuses on demographic characteristics and excludes the academic factors as included in Perna's (2006) first layer.  The second layer combined the second layers of the Crisp et al. and Perna models; the former focuses only on students' academic preparation and experiences, while the latter focuses only on school and community characteristics. The third layer combined the third and fourth layers of the Crisp et al. model and the third layer of the Perna model. Again, the Crisp et al. model focuses only on students' college experiences and academic achievements, but ignores the institutional characteristics. The Perna model focuses on institutional factors, but excludes any individual experience in the third layer.

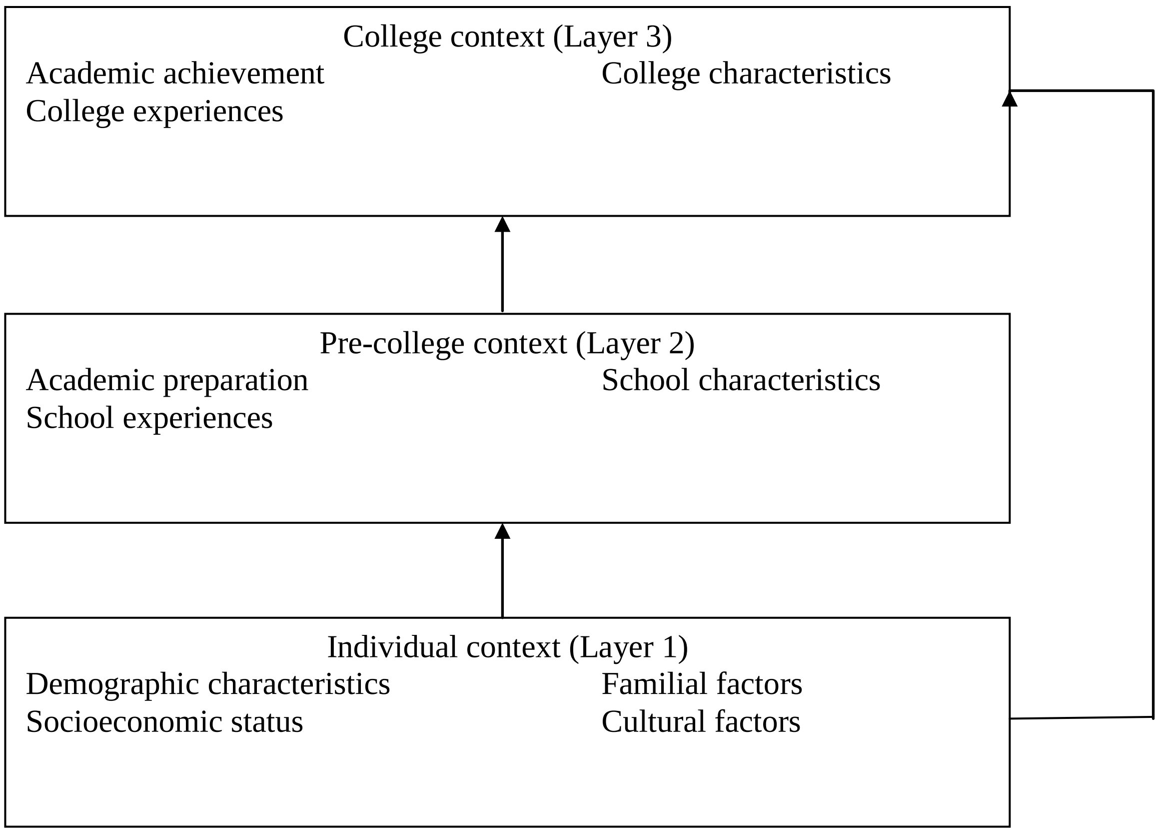



Figure 3-1. Structure of student context

The new structure followed the logic that students have characteristics that are born with them, and they find themselves in life contexts that they have little or no control over. These include their demographic characteristics, family background, parental support, and cultural background. Students then bring these characteristics into the educational context, where individual factors interact with institutional characteristics to shape educational outcomes. Through each layer, students are defined and developed, and their individual factors are carried with them into the next layer. Individual factors prepare for pre-college experiences, while pre-college context prepares for college experiences, including college major choice. As shown in Figure 3-1, students' individual factors influence their college experiences both directly and indirectly through pre-college context. Since students' progress in the educational system is a one-direction flow of actions, the influences are one-direction as well. In the following subsections, I describe the independent variables selected for the data analysis. Table 3-1 provides a summary of variables included in this study.

**Individual context**

The role played by individual factors in college major choice was the focus of this study. Independent variables from the individual context were categorized into four groups. The first group referred to demographic characteristics, including gender and race/ethnicity. Numerous empirical studies have pointed to the association between gender and race/ethnicity and college major choice pattern, as discussed in Chapter Two (e.g. Kelly, 2009; Riegle-Crumb & King, 2010). Generally, male, Asian, and white students are favored in choosing STEM majors, while female students and the remaining racial groups are underrepresented in STEM fields. Therefore, gender and race variables were included in the data analysis.

The second group referred to students' family socioeconomic status, which was the most important potential predictor in this study. Empirical evidence has suggested that there is association between family SES and college major choice, although findings are inconsistent (Goyette& Mullen, 2006; Ma, 2009). Conventionally, socioeconomic status is defined as a composition of education level, occupation, and income. For students, their family socioeconomic status refers to the education level,

Table 3-1. Dependent and independent variables

| Variable | Description | Variable type | Scale (r: reference) |
|---|---|---|---|
| | Dependent variable | | |
| College major | College major in STEM or non-STEM field | dichotomous | non-STEM<br>STEM |
| | Independent variables | | |
| | Individual context | | |
| Gender | Sex composite | categorical | male (r)<br>female |
| Race/ethnicity | Students' race/ethnicity composite | categorical | white (r), black, Hispanic, Asian, other race/ethnicity |
| Family SES | Family socio-economic status composite | continuous | - |
| Parental expectation | How far in school parent wants 10th grader to go composite | categorical | lower than college (r), college 4 year or lower, graduate school |
| In-home parent-child discussions | How often discussed school courses with parents | categorical | never (r), sometimes, often |
| Home learning environment | Family has more than 50 books | dichotomous | no (r), yes |
| Student expectation | Highest level of education respondent expects to complete, composite | categorical | high school or lower (r), college 4 or 2 year, graduate school, not clear |
| English as native language | Whether English is student's native language, composite | dichotomous | no (r), yes |
| Value placed on education | Special privileges given for good grades | categorical | never or rarely (r ), sometimes, often |
| | Pre-college context | | |
| Academic preparation | Most recent SAT math score | continuous | - |
| High school course taking | Math course taking pipeline | categorical | low (r), medium, high |

Table 3-1 Continued

| Variable | Description | Variable type | Scale (r: reference) |
|---|---|---|---|
| Career goal | Importance of being able to find steady work | categorical | not very important (r), very important |
| College preparation | Ever in program to help prepare for college | dichotomous | no (r ), yes |
| Quality of teacher | Highest degree earned by math teacher | categorical | Bachelor's or below (r), Master's or above |
| School SES | Grade 10 percent free lunch | continuous | - |
| | College context | | |
| Total cost of attendance | Total cost of college attendance | continuous | - |
| Financial concerns | chose school for cost | dichotomous | no (r), yes |
| Selectivity of college | Institutional selectivity | categorical | not classified (r), inclusive, moderately selective, highly selective |
| STEM program scale of college | Graduate enrollment in STEM fields | continuous | - |
| STEM program level of college | Highest degree in STEM fields | categorical | Bachelor's (r), Master's, Doctoral, professional, and others |

occupation, and income of their parents. ELS: 2002 provided both composite variable of family SES and variables of parents' education and family income. Since the composition of the three aspects best reflects a family's social and economic status, I used the composite variable *BYSES1* in ELS: 2002 as measure of family SES. This variable is constructed by the survey researchers from parent questionnaire data based on five equally weighted, standardized components: father's/guardian's education, mother's/ guardian's education, family income, father's/guardian's occupation, and mother's/guardian's occupation.  Each of these five composite variables are imputed if missing by the survey researchers.

The third group concerned familial factors, which focused on the influence of parents on students' education.  Research shows that parental support plays an important role in children's educational attainment (Ong, Phinney, & Dennis, 2006). Parental support, or "at-home" involvement, takes various forms, such as the provision of a secure and stable environment, parent-child discussion, constructive social and educational values, and high aspirations (Dennis, Phinney, & Chuateco, 2005; Desforges & Abouchaar, 2003).  Research shows that at-home involvement by parents is positively related to academic attainment, especially parental aspirations for children's achievement and in-home parent-child discussions (Singh et al., 1995).  Home learning environment, such as reading, library visits, and painting and drawing, is shown to be a strong contributor to educational success (Foster, Lambert, Abbott-Shim, McCarty, & Franze, 2005).  Based on these research findings, it was assumed that these factors might also influence students' choice of college major.  I included in this study the variables of parental expectation (how far in school parent wants student to go), in-home parent-child discussions (how often student discussed school courses with parents), and home learning environment (family has more than 50 books) from the ELS dataset to represent familial influences on students' educational attainment.

The last group of individual factors focused on cultural aspects.  Research suggests that the lack of English proficiency can lead to unequal educational resources and consequently influence students' educational outcome, such as math achievement

(Gandara, Rumberger, Maxwell-Jolly, & Callahan, 2003; Tate, 1997). The value placed on education by students' family plays a role in forming students' educational aspirations (Lopez, 2001). Students' own aspiration for educational achievement has also been shown to be associated with their eventual educational outcomes (Gorard, See, & Davies, 2012). In this study, I included the variables of English as native language (whether English is students' native language), value placed on educational attainment by parents (special privileges given for good grades), and students' own expectation for education (highest level of education student expects to complete) to reflect the cultural influence on students' educational outcome.

**Pre-college context**

Factors from the pre-college context were categorized into three groups: academic preparation, school experiences, and school characteristics. Academic preparation, especially in math, has been shown to influence students' decision of college major (Crisp, Nora, & Taggart, 2009). College preparation programs provide students with information regarding college education by organizing tutoring, mentoring, advising, college campus visits, summer programs, and educational field trips. These programs are shown to have positive influence on students' college education decisions (Cates &Schaefle, 2011). Students gradually form career goals throughout their school years, which may influence their college education trajectory. Having a job-related goal is related to positive persistence decisions by college students, suggesting that clear career goals influence students' college education decision making (Hull-Blanks et al., 2005). Research has shown that teacher quality, such as teachers' degree and course taking, is positively related to students' learning outcomes (Wayne & Youngs, 2003). School socioeconomic status is shown to have as much impact on students' academic achievements as students' own socioeconomic status, suggesting that school quality as measured by the aggregated SES level influences educational attainment (Rumberger & Palardy, 2005). In this study, I included the following variables to represent academic preparation, school experiences, and school characteristics. For academic preparation, I included the most recent SAT math score and the highest math course in high school. For school experiences, I included college preparation program participation (ever in program to help prepare for college) and career goal (importance of being able to find steady work). For school characteristics, I included quality of teacher (highest degree earned by math teacher) and school SES (percent of grade 10 students in free lunch program, categorical).

**College context**

Factors related to college context were categorized into three groups: academic achievement, college experiences, and college characteristics. In this study, the focus of college context factors was placed on students' college experiences, specifically, their financial situation related to college education. College costs and financial concerns were among the most important determinants of students' college education decision making (St. John, Paulsen, & Carter, 2005). The second research question aimed at finding out the association between students' monetary investment in college and their college major. Ideally, college investment level could be calculated as the difference between the total cost of college attendance and the grant they receive, over the total financial sources available to students. The former term measures the actual amount paid by students and their families for college education. The latter term measures the total financial means available to students and their families. The ratio of the two terms measures the difficulty of paying for college. However, after reviewing all three data sources, it can be seen that two of the three variables needed for the calculation were not available, at least not in high quality. First, there was no continuous variable of students' family income. Instead, a categorical variable that measures the level of family income was available. Second, although a variable that measures the cumulative Pell grant received by students was available from ELS, the missing rate of this variable was extremely high (73%).

Due to the high missing rate and the lack of strong predictor as auxiliary variable, the multiple imputation results of this variable did not represent the original distribution well (for results of multiple imputation, see subsection of Missing data). As a result, although the total cost of college attendance could be calculated based on related variables, it was impossible to calculate the investment level as intended when this study was first proposed. Based on these limitations, the total cost of attendance calculated on an individual basis was used as a proxy of students' monetary investment in college. I also included students' financial concern (whether they chose college for cost) as a measure of students' financial situation.

Another important indicator of students' investment in college is the college debt level. The variable that measures this amount (CNSOWED) suffers from the same problems as the grant amount variable, namely high missing rate and lack of strong predictor from the data sources. Based on the results of multiple imputation, this variable was not included in the analyses (for results of multiple imputation, see subsection of Missing data). While family means of college investment was very likely to play an important role in students' college decision making, no variable that measures family's actual contribution to college cost was available from any of the three data sources.  Proxy such as total family income could be used.  However, since family SES is the focus of this study and the SES variable from ELS is a composite based on parents' education, occupation, and income, including the variable of total family income would cause multicollinearity.  Based on this consideration, total family income was not included as independent variable.

College characteristics also play a role in students' educational attainment.  For example, college selectivity is associated with graduation rate (Horn& Carroll, 2006).  I included the selectivity of the institution to measure this factor.  The selectivity of the institution is based on the 2005 Carnegie classifications.  College size is shown to have impact on students' occupational choice and persistence decisions (Kamens, 1971).  Similarly, I wanted to examine whether the size and level of the STEM programs at an institution are related to students' major decision.  For this purpose, I included the variables STEM program scale (enrollment in STEM fields at both undergraduate and graduate level) and STEM program level (highest degree in STEM fields).  Academic achievement in college, especially in the first year, is shown to influence students' subsequent decisions regarding college education (Crisp, Nora, & Taggart, 2009).  However, no variable was available in any of the three data sources that measures students' academic achievement in the first semesters in college.  Therefore, this aspect was not examined in this study.

## Analytic Methods

In this section, I describe the statistical models used in this study, explain why such models are selected, describe how the models are built and then discuss the regression diagnostics procedures.  Next, I discuss the issue of missing data and present the method I use to handle missing data. Lastly, I describe the considerations about model estimation.

**Statistical Model**

The dependent variable was dichotomous: enrollment in STEM majors or non-STEM majors. As Allison (1999) shows, a dichotomous dependent variable violates the assumptions of homoscedasticity and normality of the error term for linear regression model. Consequently, the estimates of the standard error will not be consistent estimates of the true standard errors, and the coefficient estimates will no longer be efficient. In addition, estimating a linear probability model with OLS will lead to predicted values that are outside the plausible range of the probability (0,1). For these reasons, logistic regression model is used when the dependent variable is dichotomous. Logistic regression model transforms the probability to odds and then take the logarithm of the odds. In this way, both the lower and upper bound of the probability is removed. The model takes the form of the following (Allison, 1999, p. 13):

$$\log \left[ \frac{p_i}{1-p_i} \right] = \alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} \qquad 3\text{-}1$$

where pi represents the probability of the dependent variable equals one of the two levels of the dichotomous outcome variable, 1- pi represents the probability of the dependent variable equals the other of the two levels of the outcome variable, the ratio of the two represents the odds of the event, and the left-hand side expression represents the log-odds, or the logit. On the right-hand side of the equation, α represents the intercept, β represents the regression coefficient, and x represents independent variable. In logistic regression model, the relationship between the probabilities and the set of independent variables is not linear; it is the relationship between the logit and the set of independent variables that is linear. One common method of estimation for logistic regression model is maximum likelihood. The principle of this method is to choose those parameter values that would maximize the probability of observing the actual observed data. For this study, the logistic regression model is as follows:

$$\text{logit}(p_i) = \alpha + \beta 1(\text{gender}) + \beta 2(\text{race}) + \beta 3(\text{SES}) + \ldots + \beta n(xn) \quad \text{3-2}$$

where logit ($p_i$) represents the log of the odds of choosing a STEM major in college, $\alpha$ represents the intercept, $\beta$ represents the regression coefficient, and x represents the independent variable.

Block entry, or hierarchical multiple regression, was used to build the models. With this method, independent variables are grouped into blocks and entered into the model in steps (Gliner & Morgan, 2000). By estimating several models, the change in estimating the fitted model compared to the null model can be decided and attributed to the newly added group of independent variables. The grouping of variables and order to enter variables into the model are determined by the researcher's evaluation of factors such as psychometric consideration, theoretical reasons, and/or conceptualization of the research questions (Gliner & Morgan). Variables that are to be controlled for tend to be entered into the model first.

In this study, independent variables were grouped based on the discussion in the previous section. Three blocks of independent variables corresponded to the three contexts of students, namely the individual context, pre-college context, and college context. The three blocks of independent variables were added to the model in succession. A fourth block that consists of interaction terms of independent variables was added last.

Table 3-2. Multicollinearity diagnostics

| Variable | DF | Tolerance | Variance Inflation |
|---|---|---|---|
| Intercept | 1 | . | 0 |
| f2sex (gender) | 1 | 0.84 | 1.19 |
| byrace_r (race) | 1 | 0.53 | 1.89 |
| byparasp (parental expectation) | 1 | 0.79 | 1.27 |
| bys86a (discussion with parents) | 1 | 0.84 | 1.18 |
| bys84h (more than 50 books at home) | 1 | 0.83 | 1.21 |
| f2stexp (student expectation) | 1 | 0.85 | 1.17 |
| bystlang (native language) | 1 | 0.48 | 2.08 |
| bys85c (special privilege for good grades) | 1 | 0.78 | 1.29 |
| f1rmapip (highest level math course) | 1 | 0.54 | 1.85 |
| bys54e (importance of finding steady job) | 1 | 0.92 | 1.08 |
| bys33l (college preparation program) | 1 | 0.90 | 1.12 |
| bytmhdeg (highest degree of math teacher) | 1 | 0.92 | 1.09 |
| f2b13c (chose school for cost) | 1 | 0.79 | 1.27 |
| F2ISELC (college selectivity) | 1 | 0.48 | 2.09 |
| STEMLEVL (level of STEM offerings) | 1 | 0.53 | 1.88 |
| byses1 (family SES) | 1 | 0.72 | 1.38 |
| txsatm (SAT math score) | 1 | 0.51 | 1.96 |
| F1A22A (high school free/reduced lunch percentage) | 1 | 0.76 | 1.31 |
| cnsowed (consolidated debt) | 1 | 0.93 | 1.08 |
| STEMSCAU (STEM degree, undergraduate) | 1 | 0.24 | 4.23 |
| STEMSCAG (STEM enrollment, graduate) | 1 | 0.25 | 3.99 |
| TOTCOST (cost of attendance) | 1 | 0.59 | 1.71 |

**Regression Diagnostics**

Like ordinary linear regression, logistic regression requires regression diagnostics in order for the analysis to be valid. Logistic regression assumes that the logit of the outcome variable is a linear combination of the independent variables (Menard, 2002). I tested for linearity using the Box-Tidwell transformation (Hosmer & Lemeshow, 1989). This method adds a term of the form x times ln (x) to the model. If the coefficient for this variable is significant, it indicates that non-linearity exists in the logit. Results of the test suggest that linearity was met for independent variables included in the analyses.

Multicollinearity refers to the fact that two or more independent variables are highly correlated with one another (Allison, 1999). It is one common issue that may influence the results of logistic regression. Multicollinearity may lead to unstable estimates of the coefficients, inflated standard errors, and erroneous inferential conclusions. Two commonly used measures of multicollinearity are tolerance and variance inflation factor, or VIF. Tolerance of one variable is calculated as 1 minus the $R^2$ that results from the regression of other independent variables on this particular variable. VIF is the reciprocal of the tolerance. If one variable is highly correlated with the other independent variables, then the $R^2$ will be large and the tolerance will be small. Correspondingly, the VIF of this variable will be large. While there is no strict cutoff for the level of acceptable tolerance and VIF, Allison (1999) suggests investigating any variable with tolerance lower than 0.40. The tolerance and VIF of the independent variables are presented in table 3-2.

As can be seen from the table, the tolerances of two variables, STEMSCAU and STEMSCAG, are lower than 0.40. These two variables measure college's STEM major offerings at the undergraduate and graduate level, respectively. I then looked at the correlation matrix of the independent variables. It can be seen from the correlation coefficients of the two variables with other independent variables as shown in Table 3-3 and Table 3-4 that STEMSCAU and STEMSCAG are highly correlated to each other. A common method to handle multicollinearity is to drop one of the variables that cause the issue (Allison, 1999). Which variable to drop could be an arbitrary decision based on theoretical considerations. Since I was interested in how graduate level STEM offerings are associated with students' undergraduate major choice, I decided to delete the variable measuring undergraduate STEM offerings (STEMSCAU) from the analysis.

Table 3-3. Correlation coefficients of STEMSCAU with other independent variables

| | f2sex | byrace_r | byparasp | bys86a | bys84h |
|---|---|---|---|---|---|
| correlation coefficient | -0.05 | -0.09 | 0.08 | 0.02 | 0.04 |
| p-value | 0.0004 | <.0001 | <.0001 | 0.21 | 0.01 |
| | f2stexp | bystlang | bys85c | f1rmapip | bys54e |
| correlation coefficient | 0.08 | -0.14 | -0.06 | 0.24 | -0.01 |
| p-value | <.0001 | <.0001 | 0.0004 | <.0001 | 0.46 |
| | bys33l | bytmhdeg | f2b13c | f2iselc | stemlevl |
| correlation coefficient | -0.02 | -0.01 | 0.03 | -0.42 | 0.53 |
| p-value | 0.23 | 0.37 | 0.02 | <.0001 | <.0001 |
| | byses1 | txsatm | f1a22a | cnsowed | stemscau |
| correlation coefficient | 0.11 | 0.31 | -0.04 | 0.07 | 1.00 |
| p-value | <.0001 | <.0001 | 0.01 | 0.0009 | - |
| | stemscag | totcost | | | |
| correlation coefficient | 0.85 | -0.08 | | | |
| p-value | <.0001 | <.0001 | | | |

**Missing Data**

Another common issue with educational research data, especially with large-scale survey data, is the incompleteness of the data, or missing data. The issue of missing data refers to the fact that some of the data are not collected or recorded, even though they are supposed to be included in the dataset. This occurs for various reasons, for example the participants do not respond to certain items or the response is not entered into dataset by mistake. Regardless of the reason, missing data present a challenge for users of the data. Conventional methods to handle this issue include listwise deletion, pairwise deletion, dummy variable adjustment, single imputation, arithmetic mean imputation, regression imputation, averaging the available items, and last observation carried forward, among others (Allison, 2002; Enders, 2010). Although easy to implement, these methods may also lead to undesirable outcomes such as biased estimates of the coefficients and standard errors, reduced statistical power, and/or increased cost of data collection.

Table 3-4. Correlation coefficients of STEMSCAG with other independent variables

| | f2sex | byrace_r | byparasp | bys86a | bys84h |
|---|---|---|---|---|---|
| correlation coefficient | -0.03 | -0.14 | 0.11 | 0.05 | 0.05 |
| p-value | 0.03 | <.0001 | <.0001 | 0.005 | 0.005 |
| | f2stexp | bystlang | bys85c | f1rmapip | bys54e |
| correlation coefficient | 0.12 | -0.16 | -0.07 | 0.25 | -0.02 |
| p-value | <.0001 | <.0001 | <.0001 | <.0001 | 0.36 |
| | bys33l | bytmhdeg | f2b13c | f2iselc | stemlevl |
| correlation coefficient | -0.04 | 0.02 | 0.02 | -0.38 | 0.54 |
| p-value | 0.03 | 0.19 | 0.20 | <.0001 | <.0001 |
| | byses1 | txsatm | f1a22a | cnsowed | stemscau |
| correlation coefficient | 0.12 | 0.33 | -0.05 | 0.05 | 0.85 |
| p-value | <.0001 | <.0001 | 0.005 | 0.02 | <.0001 |
| | stemscag | totcost | | | |
| correlation coefficient | 1.00 | -0.001 | | | |
| p-value | - | 0.96 | | | |

To overcome the problems related with the above-mentioned methods, more advanced approaches have been developed to handle missing data. Maximum likelihood methods and multiple imputation are the most recommended methods given the current computation capacities. In this study, I adopted multiple imputation to handle the issue of missing data. The basic idea of multiple imputation is to predict the missing values by using the available values of other variables (Wayman, 2003). In multiple imputation, missing values are predicted using both variables that will be included in the analysis and variables that help predict the missing values but will be excluded from the actual analysis. The latter is called auxiliary variable. The process consists of two steps, an imputation step (I-step) and a posterior step (P-step). In the imputation step, a set of regression equations are built to impute the missing values from the observed variables. In the posterior step, random residual term is added to the mean vector and covariance matrix estimated from the filled-in data from the preceding imputation step to generate a new set of parameter values. In this way, the imputation procedure is repeated multiple times to generate several copies of imputed data, each containing unique estimates of the missing values (Enders, 2010). After the imputation

Table 3-5. Missing rate of potential independent variables

| Independent variable | Missing data rate |
|---|---|
| Race/ethnicity | 3.67 |
| In-home parent-child discussions | 13.60 |
| Home learning environment | 9.94 |
| English as native language | 3.67 |
| Value placed on education | 12.47 |
| High school course taking | 6.27 |
| Career goal | 6.47 |
| College preparation | 8.78 |
| Quality of teacher | 14.78 |
| Financial concerns | 0.11 |
| Family SES | 3.67 |
| Academic preparation | 36.03 |
| School SES | 15.83 |
| Debt level | 46.99 |
| STEM program scale of college, graduate | 0.18 |
| Total cost of attendance | 32.83 |
| cumulative Pell grant | 72.68 |

of several sets of data, regular analyses are performed using each of the datasets and the results are pooled to yield final results.

Compared to traditional methods and maximum likelihood methods, multiple imputation has several strengths. It produces estimates that are consistent and efficient. It can be used with any kind of data and model, and does not necessarily require specialized software to be carried out. To maintain a sample size as large as possible, I used multiple imputation to fill in the missing values in this study. .

**Missing data of this study**

This study merged the data from three large scale national datasets, the ELS: 2002, IPEDS, and GSS. Missing data were not exceptional in these datasets, resulting in incomplete analysis data. Of the 22 potential independent variables, only five variables had complete data. The missing data rate of the other 17 variables ranged from 0.11% to 73%. Four of the variables had missing data rate above 30%. While such missing rate is considered high, literature suggests that multiple imputation could yield more accurate estimates than traditional methods of missing data when the missing rate is moderate to high (Choi, Nam, & Kwak, 2004). Table 3-5 shows the missingness of these variables.

**Software and auxiliary variables**

Many standard statistical softwares, such as SAS and SPSS, have developed the function of multiple imputation. For example, the SAS procedure Proc MI, can perform multiple imputation by drawing from a multivariate normal distribution of all the variables in the imputation model (Little & Rubin, 2002). This method is suitable for both continuous and categorical variables with missing values to be imputed; however, the way it handles categorical variables is ad hoc, namely to round the imputed value of categorical variables (Allison, 2002). With the development of statistical methods and computer capacities, it is now recommended to avoid this method when handling categorical variables (Enders, 2010). Instead, multiple imputation by chained equations (MICE) is advocated to be more suitable for this purpose. This method is also called sequential regression multiple imputation or fully conditional specification. Instead of fitting one large multivariate normal imputation model for all variables, this method builds a series of univariate regression models based on the type of the variable to be imputed (Raghunathan, Lepkowski, Hoewyk, & Solenberger, 2001). When the dataset includes many categorical variables, the chained equations approach is more appealing than the standard imputation method.

Since ten of the independent variables with missing data were categorical, the chained equations approach was used rather than the method available in SAS Proc MI. IVEware was used to conduct the multiple imputation. IVEware is the imputation and variance estimation software developed at the University of Michigan's Survey Research Center (University of Michigan, 2011). It imputes missing data using the sequential regression imputation method. Typically, a total of five imputations would be sufficient, although it is preferable to perform a larger number of imputations, especially when it is relatively easy to implement with advanced computing techniques (Allison, 2002). For this study, a total of ten imputations were performed.

One of the advantages of multiple imputation is that it not only uses information from variables to be included in the analyses, but also uses information from variables that are not of interest to the researcher but are predictive of the variables to be imputed. Therefore, selecting a set of auxiliary variables is important to the multiple imputation process (Enders, 2010). The datasets used in this study are longitudinal, providing sources of variables that are correlated to the independent variables to be included in the analyses. I selected a set of auxiliary variables using the following principles: that the auxiliary variable measures the same content as the independent variable or the auxiliary variable is conceptually related to the independent variable; that the auxiliary variable has fewer missing data than the independent variable or has a different missing pattern than the independent variable. The number of auxiliary variables included in the imputation was not limited, as there is no disadvantage of including as many auxiliary variables as possible (Rubin, 1996).

**Results of imputation**

The distribution of variables with missing values was compared before and after the imputation. The imputed data represent the original distribution of all variables except for PELLCUM (cumulative Pell grant received) and CNSOWED (consolidated loan: amount owed). The missing rate of PELLCUM is 73%. The mean is 5358, the standard deviation is 3316, and the median is 5150. The imputed data has a different distribution. For one of the imputations, the variable PELLCUM has a mean of 4780, a standard deviation of 3022, and a median of 4400. The missing rate of CNSOWED is 46.99%. The mean is 597, the standard deviation is 2054, and the median is 0. The imputed data has a different distribution. For one of the imputations, the variable CNSOWED has a mean of 1269, a standard deviation of 1956, and a median of 139. Figure 3-2 and figure 3-3 show the distributions of the original and the imputed variables.

As can be seen from Figure 3-2, it is clear that the imputed variable has a different distribution compared to the variable before imputation. This is likely because of the high missing rate of the variable and because of the lack of strong predictor(s) of

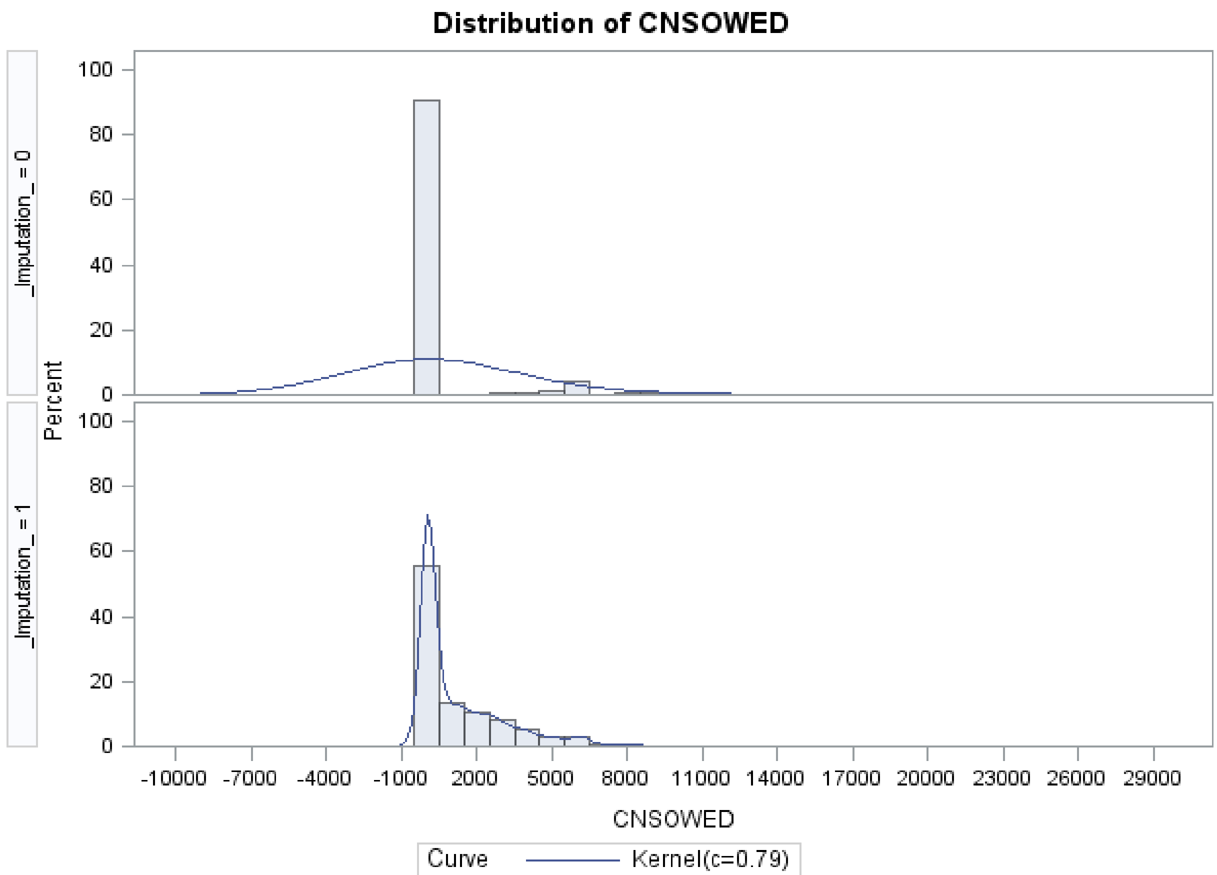



Figure 3-2. Distribution of variable CNSOWED before and after imputation

CNSOWED. The only available auxiliary variable that may predict CNSOWED is a variable that measures the amount students borrow for undergraduate loans. Although these two variables measure similar content, one of them is self-reported while the other is drawn from the National Student Loan Data System. In addition, the auxiliary variable itself has a high missing rate as well (55%). Because of these reasons, the imputation of CNSOWED did not yield values that represent the original distribution. Thus, I decided not to include CNSOWED in the analyses. The variable PELLCUM also suffers from the same problems and was not included in the analyses.

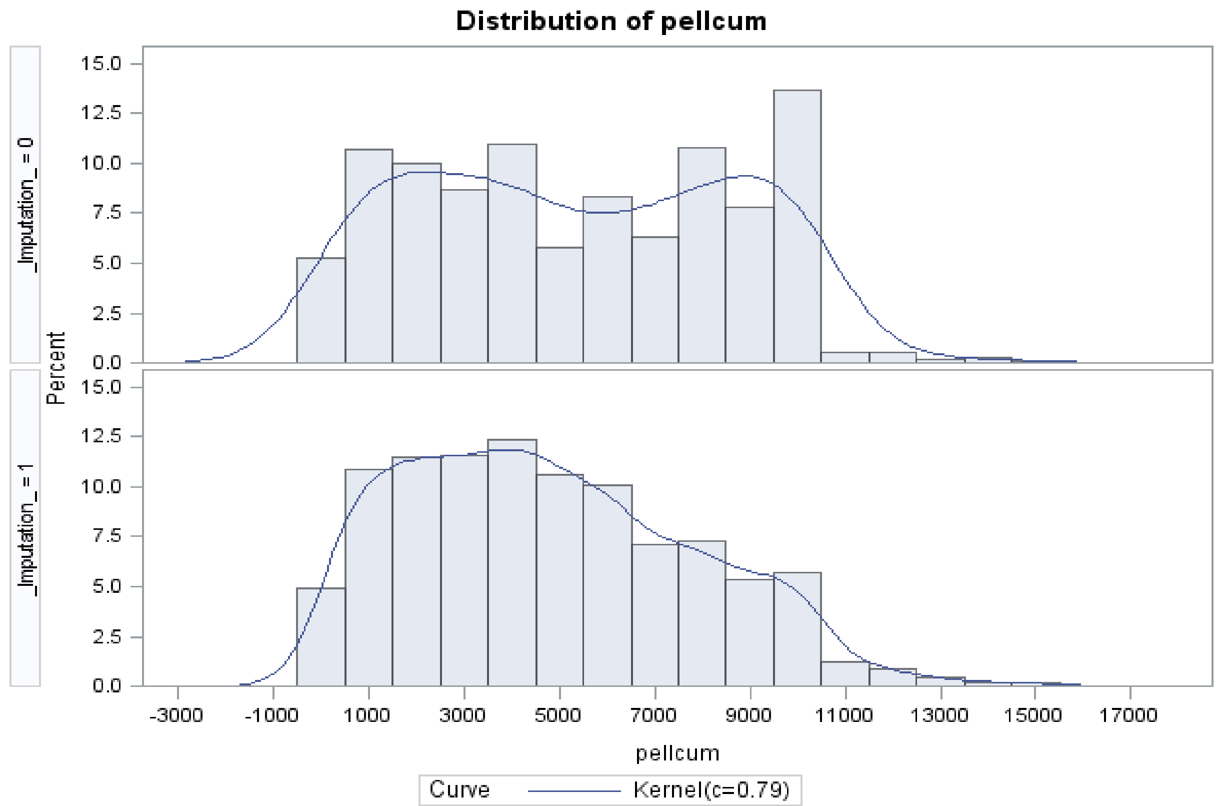



Figure 3-3. Distribution of variable PELLCUM before and after imputation

**Model Estimation**

The ELS data are collected using complex survey methods. Thus, I needed to consider the survey design when analyzing the data in order to compensate for effects such as unequal probability of selection and stratification. Ignoring the design effects would lead to inconsistent estimation of parameters and/or standard errors and consequently erroneous inferential conclusions (Wang, Yu, & Lin, 1997). For the analysis of complex survey data, two types of methods could be used. Design based methods account for the effect of complex survey design such as stratification and clustering by adjusting the standard errors. Common design based methods include Taylor-series approximation, bootstrapping, jackknife repeated replication, and design effects. Model based methods incorporate the complex survey design effects in the statistical model in order to obtain unbiased standard errors. The most common model based methods are hierarchical linear models and multilevel structural equation models. Research has shown that results obtained from design based methods and model based methods are highly comparable (Ghoshl & Pahwa, 2006).

In this study, design based method was adopted with the weight variable. This method removes bias, which is the main concern for complex survey data. The main analyses were performed using SAS. The survey design effects were accounted for by using the SAS procedure *surveylogistic*. This procedure performs logistic regression while taking into account the design effects common to large scale survey data. Taylor-series linearization is used by this procedure to obtain unbiased standard errors. Information about the stratum, cluster, and weight is provided in the ELS data user's manual (Ingels et al., 2007). The weight provided in the user's manual was normalized in order for the sum of the weight to equal the sample size rather than the population size.

In ordinary linear regression, the primary measure of model fit is $R^2$, which measures the percentage of variance in the dependent variable that is explained by fitting the model. In logistic regression, several measures can be used to assess the goodness of fit of the model. These include classification tables, Hosmer-Lemeshow test, and pseudo $R^2$s. Hosmer-Lemeshow test is a significance test, which only reveals whether the model fits but does not reveal the extent of the fit. In this study, the generalized pseudo $R^2$ reported by the SAS procedure *surveylogistic* was used to assess the goodness of fit of the models (Nagelkerke, 1991).

## Limitations of the Study

The first limitation of this study was that certain key measures are not available from the data sources.  In order to calculate the individual investment level, information of students' family income and grant amount is crucial.  Because these measures are not available with acceptable quality, it was not impossible to calculate the college cost as a proportion of family income, which would yield more accurate information than the amount of college attendance cost itself.  The second limitation was related to the self-reported variables, such as frequency of parent-child discussion.  While such information could only be obtained from individuals, their responses are subject to inaccurate recall of facts or influence of social desirability (Marlowe & Crowne, 1961). This limitation was mainly related to the variables that measure students' individual context.

CHAPTER 4
DATA ANALYSIS AND RESULTS

In this chapter, I discuss the findings related to each of the research questions. First, I present the descriptive statistics and preliminary analyses that examine the independent variables and group differences. Next I present the logistic regression analyses and model results. I conclude the chapter with a summary of the findings.

## Preliminary Data Analysis

In this section, I present descriptive statistics of the analyses sample. Next I present the findings from the statistical tests used to examine group differences on independent variables.

### Descriptive Statistics

Table 4-1. Demographics of analyses sample by major choice (N=4,500)

| | Non-STEM major | STEM major |
|---|---|---|
| Gender | | |
| Male | 37.72% | 62.13% |
| Female | 62.28% | 37.87% |
| Race | | |
| White | 67.93% | 60.08% |
| Black | 10.11% | 10.91% |
| Hispanic | 8.03% | 6.78% |
| Asian | 9.35% | 17.70% |
| Other (American Indian/Alaska Native, non-Hispanic, more than one race, non-Hispanic, Native Hawaii/Pacific Islander, non-Hispanic) | 4.58% | 4.51% |
| Native language | | |
| English | 88.81% | 80.73% |
| Non-English | 11.19% | 19.27% |

Table 4-1 presents the demographics of the analyses sample by college major choice. Male students (62.13%) are more likely to choose STEM major than female students (37.87%). Asian students' share in STEM majors (17.70%) is higher than their share in non-STEM majors (9.35%), while the opposite holds for white students

(67.93% in non-STEM majors and 60.08% in STEM majors) and Hispanic students (8.03% in non-STEM majors and 6.78% in STEM majors). Students whose native language is not English have a larger share in STEM majors (19.27%) than in non-STEM majors (11.19%). These findings are consistent with prior findings that male, Asian, and students who lack cultural capital tend to be more likely to choose STEM major in college (Xie & Goyette, 2003). Figures 4-1 to 4-3 show the distribution of major groups by gender, race, and native language, respectively.

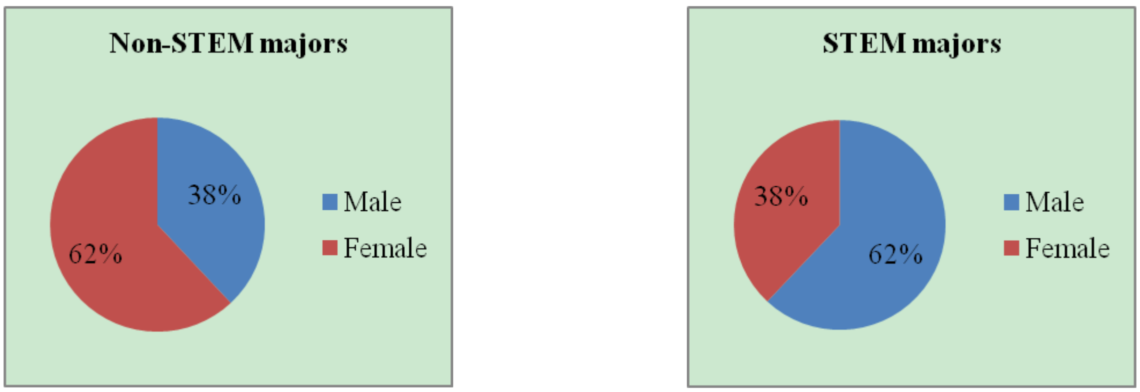



Figure 4-1. STEM and non-STEM majors by gender

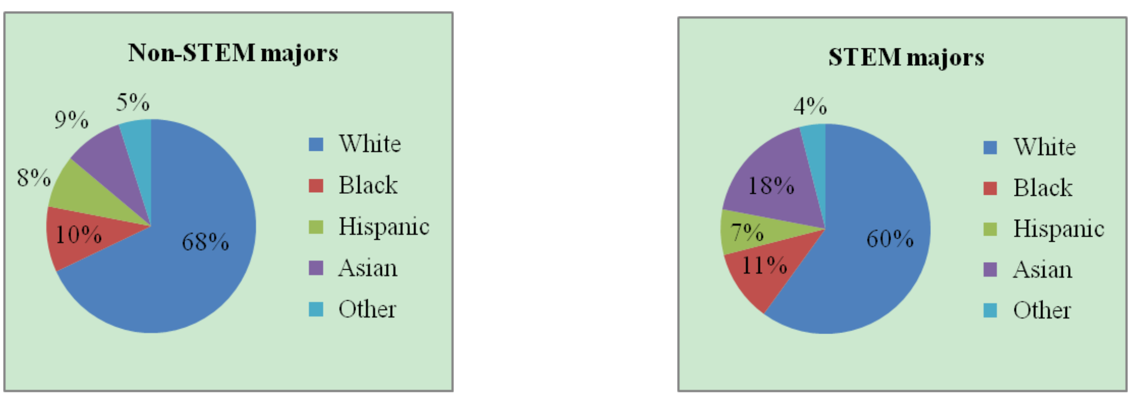
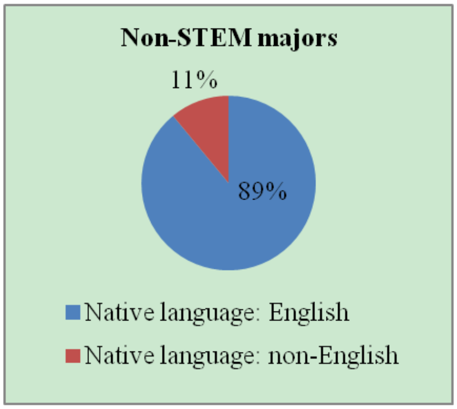



Figure 4-2. STEM and non-STEM majors by race



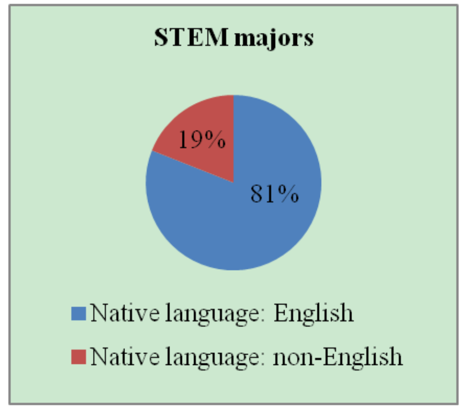




Figure 4-3. STEM and non-STEM majors by native language

Table 4-2. Percentage/mean (standard deviation) of individual context independent variables by major choice

| | Non-STEM major | STEM major |
|---|---|---|
| Family SES | 0.42 (0.68) | 0.48 (0.71) |
| Parental expectation | | |
| Lower than college | 0.73% | 0.65% |
| College, 4 year or lower | 43.16% | 33.78% |
| Graduate school | 56.11% | 65.58% |
| In-home parent-child discussions | | |
| Never | 10.16% | 11.53% |
| Sometimes | 51.20% | 47.03% |
| Often | 38.64% | 41.43% |
| Home learning environment | | |
| More than 50 books at home | 91.33% | 90.71% |
| No more than 50 books at home | 8.67% | 9.29% |
| Student expectation | | |
| High school or lower | 0 | 0 |
| College, 4 or 2 years | 32.93% | 26.12% |
| Graduate school | 64.99% | 71.46% |
| Not clear | 2.07% | 2.43% |
| Value placed on education | | |
| Never or rarely given special privileges for good grades | 32.31% | 36.88% |
| Sometimes given special privileges for good grades | 35.41% | 36.32% |
| Often given special privileges for good grades | 32.28% | 26.80% |

Table 4-2 shows the percentage/mean (standard deviation) of individual context independent variables by major choice. As can be seen, the average family SES is higher for students who choose STEM majors (0.48) than those who choose non-STEM majors (0.42). Students whose parents expect them to attend graduate school have a larger share in STEM majors (65.58%) than in non-STEM majors (56.11%). Students who expect themselves to attend graduate school also have a larger share in STEM majors (71.46%) than in non-STEM majors (64.99%). Students who expect themselves to attend no higher than undergraduate college have a smaller share in choosing STEM majors (26.12%) than choosing non-STEM majors (32.93%). Students who are often given special privileges for good grades have a smaller share in choosing STEM majors (26.80%) than choosing non-STEM majors (32.28%), while students who are never or rarely given special privileges have a larger share in choosing STEM majors (36.88%) than choosing non-STEM majors (32.31%). Students who often discuss school courses with parents have a larger share in choosing STEM majors (41.43%) than choosing non-STEM majors (38.64%), while the opposite holds for students who only sometimes

Table 4-3. Percentage/mean (standard deviation) of pre-college context independent variables by major choice

| | Non-STEM major | STEM major |
|---|---|---|
| Most recent SAT math score | 539 (101) | 599 (98) |
| High school math course taking pipeline | | |
| Low | 0.73% | 0.4% |
| Medium | 22.91% | 9.29% |
| High | 76.37% | 90.32% |
| Importance of being able to find steady work | | |
| Not very important | 11.41% | 11.53% |
| Very important | 88.59% | 88.47% |
| Ever in program to help prepare for college | | |
| No | 75.60% | 76.13% |
| Yes | 24.40% | 23.87% |
| Highest degree earned by math teacher | | |
| Bachelor’s or below | 47.35% | 47.40% |
| Master’s or above | 52.65% | 52.61% |
| Percent of grade 10 student body receiving free/reduced-price lunch | 19.09 (22.78) | 20.04 (21.98) |

discuss school courses with parents (47.03% in choosing STEM majors and 51.20% in choosing non-STEM majors). Students' major choice does not seem to differ by the amount of books at home.

Table 4-3 shows the percentage/mean (standard deviation) of pre-college context independent variables by major choice. As can be seen, students who choose STEM majors have an average SAT score (599) much higher than those who choose non-STEM majors (539). Among those who major in STEM fields, 90.32% of the students have finished high level math course in high school, while only 76.37% of the students who choose non-STEM majors have finished such courses. The percentage of students across different levels of career goal, college preparation program participation, and highest degree earned by math teacher are very similar for students majoring in STEM and non-STEM fields. In addition, students with different major choices come from high schools with similar average SES level.

Table 4-4. Percentage/mean (standard deviation) of college context independent variables by major choice

| | Non-STEM major | Stem major |
|---|---|---|
| Total cost of attendance | 20,832 (9,564) | 20,011 (8,792) |
| Chose school for cost | | |
| No | 50.42% | 47.61% |
| Yes | 49.58% | 52.39% |
| Selectivity of college | | |
| Not classified | 5.34% | 4.57% |
| Inclusive | 10.57% | 7.74% |
| Moderately selective | 46.92% | 38.53% |
| Highly selective | 37.17% | 49.16% |
| Graduate enrollment in STEM fields | 727 (1,075) | 1,184 (1,334) |
| Highest degree in STEM fields offered by institute | | |
| Bachelor's | 25.90% | 17.54% |
| Master's | 26.34% | 18.38% |
| Doctoral, Professional, and others | 47.77% | 64.09% |

Table 4-4 shows the percentage/mean (standard deviation) of college context independent variables by major choice. As can be seen, the average total cost of attendance of colleges attended by non-STEM major students (20,832) is higher than that of colleges attended by STEM major students (20,011). Among students who major in STEM fields, 52.39% chose college based on cost concerns, while the percentage among non-STEM students is lower (49.58%). Among students who major in STEM fields, the share of those enrolling in highly selective colleges is 49.16%. Among those who major in non-STEM fields, such share is 12% lower at 37.17%. On the other hand, the proportion of non-STEM students who attend colleges that are inclusive or moderately selective (57.49%) is higher than the proportion of STEM students (46.27%) who attend inclusive or moderately selective colleges. The average number of graduate enrollment in STEM fields at colleges attended by STEM students (1,184) is much higher than that of colleges attended by non-STEM students (727). Among STEM students, 64.09% enroll at colleges that offer doctoral degrees in STEM fields, 18.38% enroll at colleges that offer Master's degrees in STEM fields, and 17.54% enroll at colleges that offer no higher than Bachelor's degree in STEM fields. Among non-STEM students, 47.04% enroll at STEM doctorate conferring colleges, 26.34% enroll at STEM Master's degree conferring colleges, and 25.90% enroll at STEM Bachelor's degree conferring colleges. The findings suggest that STEM students are more aggregated in institutes with high selectivity, and larger and higher level STEM degree offerings, while the opposite holds for non-STEM students. Non-STEM students pay more for college on average than STEM students, and choose college for cost less frequently than STEM students.

### Group Differences on Independent Variables

While the descriptive statistics suggest that STEM and non-STEM students differ on various independent variables, statistical tests of group differences were needed to examine whether the observed differences between the two groups are due to statistically significant group differences or merely by chance. I used t-tests and chi-squared tests to examine the group differences between STEM and non-STEM students.

Table 4-5. Chi-squared tests for STEM and non-STEM student groups

| Independent variable | DF | Pearson chi-square | p-value |
|---|---|---|---|
| Gender | 1 | 197.80 | <.0001 |
| Race | 4 | 57.26 | <.0001 |
| Parental expectation | 2 | 30.16 | <.0001 |
| In-home parent-child discussions | 2 | 4.99 | 0.08 |
| Family has more than 50 books | 1 | 0.35 | 0.55 |
| Student expectation | 2 | 17.71 | 0.0001 |
| Whether English is student's native language | 1 | 44.67 | <.0001 |
| Whether receive special privileges for good grades | 2 | 11.24 | 0.0036 |
| Highest level of mathematics completed in high school | 2 | 92.65 | <.0001 |
| Importance of being able to find steady work | 1 | 0.01 | 0.92 |
| Ever in program to help prepare for college | 1 | 0.11 | 0.74 |
| Highest degree earned by math teacher | 1 | 0.0005 | 0.98 |
| Chose college for cost | 1 | 2.57 | 0.11 |
| Institutional selectivity | 3 | 49.68 | <.0001 |
| Highest degree in STEM fields | 2 | 87.13 | <.0001 |

Table 4-5 presents the results of chi-squared tests of group differences on categorical independent variables. There are statistically significant differences between STEM and non-STEM students on most of the independent variables selected for this study. STEM and non-STEM students differ strongly on gender, race, the level of education parents expect students to complete, whether students' native language is English, highest level of mathematics completed in high school, the selectivity of college enrolled in, and the highest degree in STEM fields offered by college enrolled in (p-value <.0001). Student expectation of education level also varies strongly for STEM and non-STEM students, with a p-value of 0.0001. The two groups also differ strongly on whether they receive special privileges for good grades, with a p-value of 0.0036. The group differences of STEM and non-STEM students on the frequency of school course discussion with parents are statistically significant at the .10 level (p-value=0.08). The difference between the two groups of students on whether they chose college for cost reasons is statistically insignificant, although the p-value (0.11) approaches the .10 significance level. STEM and non-STEM students do not differ statistically significantly on the number of books at home, the importance of being able to find steady work, participation in college preparation programs in high school, and the highest degree earned by their math teachers in high school.

Table 4-6. Independent samples t-tests for non-STEM and STEM student groups

| Independent variable | t | p-value |
|---|---|---|
| Family SES | -2.47 | 0.01 |
| SAT math score | -14.09 | <.0001 |
| Percentage of student body receiving free/reduced-price lunch at high school | -1.09 | 0.27 |
| Graduate enrollment in STEM fields | -10.74 | <.0001 |
| Total cost of college attendance | 2.03 | 0.04 |

Table 4-6 presents the results of the independent samples t-tests of group differences on continuous independent variables. As can be seen, STEM and non-STEM students differ on family SES, SAT math score, total cost of college attendance, and STEM enrollment on the graduate level at the institutions they attend. On average, students who choose STEM majors have higher family SES and higher SAT math score then those who choose non-STEM majors. STEM students attend colleges with lower cost of attendance and higher enrollment in STEM fields on the graduate levels. STEM and non-STEM students do not differ statistically significantly on the percentage of student body receiving free-reduced-price lunch at high school.

### Inferential Analysis

Descriptive statistics and group difference tests show that STEM and non-STEM students differ by several characterisitcs including gender, race, native language, parental support, academic preparation, family SES, institutional cost and selectivity,

Table 4-7. Logistic regression results: individual context variables

| Parameter | Estimate | Std Error | t for H0 | Pr > \|t\| | Estimated odds ratio |
|---|---|---|---|---|---|
| Intercept | -0.21 | 0.65 | -0.32 | 0.75 | 0.81 |
| family SES | 0.02 | 0.08 | 0.2 | 0.84 | 1.02 |
| female | -1.15 | 0.09 | -12.62 | <.0001 | 0.32 |
| other racial groups | 0.07 | 0.25 | 0.3 | 0.76 | 1.08 |
| Asian | 0.31 | 0.22 | 1.43 | 0.16 | 1.37 |
| Black | 0.25 | 0.17 | 1.45 | 0.15 | 1.28 |
| Hispanic | -0.10 | 0.19 | -0.55 | 0.58 | 0.90 |
| parental expectation: college, 4 year or lower | -0.04 | 0.53 | -0.08 | 0.94 | 0.96 |
| parental expectation: graduate school | 0.26 | 0.54 | 0.48 | 0.63 | 1.30 |
| discussion of course work: sometimes | 0.07 | 0.18 | 0.39 | 0.70 | 1.07 |
| discussion of course work: often | 0.32 | 0.19 | 1.68 | 0.10 | 1.37 |
| student expectation: college | -0.34 | 0.31 | -1.12 | 0.26 | 0.71 |
| student expectation: graduate school | -0.06 | 0.30 | -0.22 | 0.83 | 0.94 |
| special privileges given for good grades: sometimes | -0.17 | 0.11 | -1.5 | 0.14 | 0.85 |
| special privileges given for good grades: often | -0.46 | 0.14 | -3.33 | 0.001 | 0.63 |
| English is native language | -0.39 | 0.19 | -2.08 | 0.04 | 0.68 |
| family has more than 50 books | -0.03 | 0.17 | -0.15 | 0.88 | 0.98 |

Note. “Other racial groups” refer to American Indian/Alaska Native, non-Hispanic, more than one race, non-Hispanic, Native Hawaii/Pacific Islander, and non-Hispanic.

and STEM offering at college. While these results are informative, inferential analyses were needed to reveal predictors of major choice. Logistic regression models were built by entering independent variables in four blocks in succession. As discussed in Chapter three, the first three blocks consist of individual context variables, pre-college context variables, and college context variables, respectively. The fourth block consists of interaction terms.

Table 4-7 shows the results of block one analysis. When controlling for individual context variables, the probability of choosing STEM major in college is lower for women than for men (p-value <.0001). The estimated odds ratio of choosing STEM major for women to men is 0.32, suggesting that the probability of men choosing STEM major is about three times that of women. Interestingly, when students often receive special privileges given for having good grades at school, their probability of choosing STEM majors in college is lower than those who never or rarely receive such privileges (p-value=0.001). The estimated odds ratio is 0.63, suggesting that the probability of choosing STEM major for those who often receive special privileges from parents for good grades is about two thirds of that for those who never or rarely receive privileges as reward for good grades. For students whose native language is English, the probability of choosing STEM major is about two thirds of that for students whose native language is not English (p-value=0.04, and estimated odds ratio is 0.68), suggesting that students of immigrant background are more likely to choose STEM majors. Family SES is not significantly related to the probability of choosing STEM major (p-value=0.84). These results, however, were obtained without controlling for pre-college context and college context variables and should be interpreted with caution.

Table 4-8. Logistic regression results: individual context and pre-college context variables

| Parameter | Estimate | Std Error | t for H0: | Pr > \|t\| | Estimated odds ratio |
|---|---|---|---|---|---|
| Intercept | -3.54 | 1.00 | -3.56 | 0.0004 | 0.03 |
| family SES | -0.12 | 0.08 | -1.55 | 0.12 | 0.88 |
| female | -1.06 | 0.09 | -11.28 | <.0001 | 0.35 |
| other racial groups | 0.15 | 0.26 | 0.57 | 0.57 | 1.16 |
| Asian | 0.20 | 0.20 | 0.99 | 0.32 | 1.22 |
| Black | 0.61 | 0.19 | 3.3 | 0.001 | 1.85 |
| Hispanic | 0.05 | 0.21 | 0.23 | 0.82 | 1.05 |
| parental expectation: college, 4 year or lower | -0.23 | 0.57 | -0.41 | 0.68 | 0.79 |
| parental expectation: graduate school | -0.03 | 0.58 | -0.05 | 0.96 | 0.97 |
| discussion of course work: sometimes | 0.01 | 0.18 | 0.05 | 0.96 | 1.01 |
| discussion of course work: often | 0.26 | 0.19 | 1.41 | 0.16 | 1.30 |
| student expectation: college | -0.10 | 0.32 | -0.31 | 0.75 | 0.90 |
| student expectation: graduate school | -0.02 | 0.32 | -0.06 | 0.95 | 0.98 |
| special privileges given for good grades: sometimes | -0.07 | 0.12 | -0.56 | 0.57 | 0.94 |
| special privileges given for good grades: often | -0.33 | 0.15 | -2.19 | 0.03 | 0.72 |
| English is native language | -0.25 | 0.20 | -1.26 | 0.21 | 0.78 |
| family has more than 50 books | -0.22 | 0.19 | -1.17 | 0.24 | 0.80 |
| most recent SAT math score | 0.01 | 0.0008 | 6.86 | <.0001 | 1.01 |
| highest level of mathematics completed: medium | -0.58 | 0.46 | -1.26 | 0.21 | 0.56 |
| highest level of mathematics completed: advanced | 0.09 | 0.44 | 0.21 | 0.84 | 1.10 |
| finding steady work is very important | 0.19 | 0.14 | 1.32 | 0.19 | 1.20 |

Table 4-8. Continued

| Parameter | Estimate | Std Error | t for H0: | Pr > \|t\| | Estimated odds ratio |
|---|---|---|---|---|---|
| participated in college preparation program | -0.10 | 0.12 | -0.82 | 0.41 | 0.91 |
| highest degree earned by math teacher: Master's or above | -0.10 | 0.11 | -0.85 | 0.40 | 0.91 |
| percentage of student body receiving free/reduced-price lunch at high school | 0.01 | 0.002 | 3.33 | 0.001 | 1.01 |

Table 4-8 shows the results of analysis with block one and block two independent variables. When controlling for both individual and pre-college context variables, some interesting results emerged. Not surprisingly, women's likelihood of choosing STEM majors in college is still much lower than that of men (p-value <.0001, estimated odds ratio=0.35). Race appears to play a role in STEM major decision making. Black students, when controlling for individual characteristics and pre-college factors, have significantly higher probability of choosing STEM majors than white students (p-value=0.001). The estimated odds ratio of 1.85 suggests that when holding other individual characteristics and pre-college factors equal, the probability of choosing STEM major for Black students is 85% higher than the probability for white students. Similar to results from the analysis with only individual context variables, students who often receive special privileges for good grades at school are less likely to choose STEM majors compared to those who never or rarely receive such privileges (p-value=0.03, estimated odds ratio=0.72). Higher SAT math score is associated with higher probability of choosing STEM majors (p-value<0.0001). The estimated odds ratio of 1.01 suggests that when SAT math score increases by 1, the probability of

Table 4-9. Logistic regression results: individual context, pre-college context, and college context variables

| Parameter | Estimate | Std Error | t for H0 | Pr > \|t\| | Estimated odds ratio |
|---|---|---|---|---|---|
| Intercept | -3.10 | 1.02 | -3.04 | 0.003 | 0.05 |
| family SES | -0.11 | 0.08 | -1.4 | 0.16 | 0.89 |
| female | -1.06 | 0.09 | -11.22 | <.0001 | 0.35 |
| other racial groups | 0.09 | 0.26 | 0.34 | 0.73 | 1.09 |
| Asian | 0.14 | 0.20 | 0.68 | 0.50 | 1.15 |
| Black | 0.57 | 0.19 | 2.97 | 0.003 | 1.76 |
| Hispanic | 0.01 | 0.21 | 0.05 | 0.96 | 1.01 |
| parental expectation: college, 4 year or lower | -0.17 | 0.55 | -0.31 | 0.76 | 0.84 |
| parental expectation: graduate school | 0.04 | 0.56 | 0.07 | 0.95 | 1.04 |
| discussion of course work: sometimes | -0.01 | 0.19 | -0.03 | 0.97 | 0.99 |
| discussion of course work: often | 0.27 | 0.19 | 1.4 | 0.16 | 1.30 |
| student expectation: college | -0.17 | 0.35 | -0.49 | 0.63 | 0.84 |
| student expectation: graduate school | -0.07 | 0.35 | -0.21 | 0.84 | 0.93 |
| special privileges given for good grades: sometimes | -0.05 | 0.12 | -0.38 | 0.70 | 0.96 |
| special privileges given for good grades: often | -0.32 | 0.15 | -2.13 | 0.04 | 0.73 |
| English is native language | -0.21 | 0.20 | -1.06 | 0.29 | 0.81 |
| family has more than 50 books | -0.26 | 0.19 | -1.35 | 0.18 | 0.77 |
| most recent SAT math score | 0.01 | 0.0008 | 6.38 | <.0001 | 1.01 |
| highest level of mathematics completed: medium | -0.55 | 0.48 | -1.15 | 0.25 | 0.58 |
| highest level of mathematics completed: advanced | 0.13 | 0.46 | 0.29 | 0.78 | 1.14 |
| finding steady work is very important | 0.20 | 0.14 | 1.45 | 0.15 | 1.22 |
| participated in college preparation program | -0.07 | 0.12 | -0.61 | 0.54 | 0.93 |
| highest degree earned by math teacher: Master's or above | -0.10 | 0.11 | -0.88 | 0.38 | 0.91 |
| percentage of student body receiving free/reduced-price lunch at high school | 0.01 | 0.003 | 2.63 | 0.01 | 1.01 |

Table 4-9. Continued

| Parameter | Estimate | Std Error | t for H0 | Pr > \|t\| | Estimated odds ratio |
|---|---|---|---|---|---|
| total cost of college attendance | -0.00001 | 0.00001 | -1.58 | 0.12 | 0.99 |
| chose college for cost | -0.01 | 0.11 | -0.07 | 0.94 | 0.99 |
| institutional selectivity: inclusive | -0.17 | 0.28 | -0.61 | 0.54 | 0.85 |
| institutional selectivity: moderately selective | -0.34 | 0.24 | -1.43 | 0.15 | 0.71 |
| institutional selectivity: highly selective | -0.61 | 0.25 | -2.39 | 0.02 | 0.55 |
| Graduate enrollment in STEM fields | 0.0002 | 0.00005 | 4.34 | <.0001 | 1.0002 |
| highest degree in STEM fields: Master's | -0.33 | 0.15 | -2.12 | 0.03 | 0.72 |
| highest degree in STEM fields: Doctoral, professional, and others | 0.08 | 0.13 | 0.58 | 0.56 | 1.08 |

choosing STEM majors increases by one percent. Interestingly, although family SES is still insignificant (p-value=0.12), the level of students' high school SES as measured by the percentage of student body receiving free/reduced-price lunch is statistically significant (p-value=0.001). For two students whose other characteristics are held equal, the one attending a high school with a free/reduced-price lunch percentage one percent higher has a one percent higher probability of choosing STEM major in college (estimated odds ratio=1.01), suggesting that students who attend lower SES high school have a higher likelihood of choosing STEM major in college.

Table 4-9 shows the results of analysis with all three blocks of independent variables. When controlling for individual context, pre-college context, and college context factors, little change emerged in the results regarding the first two blocks of variables. Again, family SES is not statistically significant (p-value=0.16). The probability of choosing STEM majors for female students is about one third of that for male students (p-value<0.0001, estimated odds ratio=0.35). Compared to white students, the probability of enrolling in STEM majors for Black students is about 76% higher (p-value=0.003, estimated odds ratio=1.76). Students who often receive special privileges from parents for good grades are about 25% less likely to choose STEM majors in college compared to those who never or rarely receive such privileges (p-value=0.04, estimated odds ratio=0.73). SAT math score is positively related to the probability of STEM enrollment, with one point increase on the score corresponding to one percent increase of the likelihood (p-value<0.0001, estimated odds ratio=1.01). Students who come from high schools with higher percentage of students receiving free/reduced-price lunch have higher probability of enrolling in STEM majors in college (p-value=0.01, estimated odds ratio=1.01). Students enrolling in highly selective institutions are less likely to choose STEM majors (p-value=0.02, estimated odds ratio=0.55), while students enrolling in institutions with larger graduate enrollment in STEM fields are more likely to choose STEM majors (p-value<0.0001, estimated odds ratio=1.0002). Interestingly, enrolling in institutions where Master's degree is the highest degree conferred in STEM fields is negatively related to the probability of choosing STEM majors (p-value=0.03). Compared to students who enroll in institutions where Bachelor's degree is the highest degree conferred in STEM fields, the probability of choosing STEM major is 28% lower for the above-mentioned students.

After analyzing all independent variables, I added interaction terms of family SES and certain variables. One reason to do so was the observation that although family SES is not statistically significant in all three analyses, its p-value in fact approached significance at the .10 level when controlling for pre-college and college context independent variables and its estimate has been consistently negative. Another reason

Table 4-10. Logistic regression results: individual context, pre-college context, college context variables, and interaction terms

| Parameter | Estimate | Std Error | t for H0 | Pr > \|t\| | Estimated odds ratio |
|---|---|---|---|---|---|
| Intercept | -2.81 | 1.03 | -2.73 | 0.01 | 0.06 |
| family SES | -1.76 | 0.44 | -4.01 | <.0001 | 0.17 |
| female | -1.14 | 0.11 | -10.51 | <.0001 | 0.32 |
| other racial groups | 0.08 | 0.26 | 0.32 | 0.75 | 1.09 |
| Asian | 0.10 | 0.21 | 0.48 | 0.63 | 1.10 |
| Black | 0.47 | 0.19 | 2.46 | 0.01 | 1.60 |
| Hispanic | -0.07 | 0.21 | -0.32 | 0.75 | 0.94 |
| parental expectation: college, 4 year or lower | -0.04 | 0.55 | -0.06 | 0.95 | 0.97 |
| parental expectation: graduate school | 0.17 | 0.55 | 0.31 | 0.76 | 1.18 |
| discussion of course work: sometimes | -0.01 | 0.19 | -0.04 | 0.97 | 0.99 |
| discussion of course work: often | 0.27 | 0.19 | 1.4 | 0.16 | 1.31 |
| student expectation: college | -0.21 | 0.34 | -0.61 | 0.54 | 0.81 |
| student expectation: graduate school | -0.09 | 0.33 | -0.28 | 0.78 | 0.91 |
| special privileges given for good grades: sometimes | -0.05 | 0.12 | -0.43 | 0.67 | 0.95 |
| special privileges given for good grades: often | -0.31 | 0.15 | -2.11 | 0.04 | 0.74 |
| English is native language | -0.23 | 0.20 | -1.16 | 0.25 | 0.79 |
| family has more than 50 books | -0.26 | 0.19 | -1.37 | 0.17 | 0.77 |
| most recent SAT math score | 0.004 | 0.0009 | 5.13 | <.0001 | 1.004 |
| highest level of mathematics completed: medium | -0.53 | 0.48 | -1.11 | 0.27 | 0.59 |
| highest level of mathematics completed: advanced | 0.18 | 0.46 | 0.38 | 0.70 | 1.19 |
| finding steady work is very important | 0.21 | 0.14 | 1.51 | 0.13 | 1.23 |
| participated in college preparation program | -0.07 | 0.12 | -0.58 | 0.56 | 0.93 |
| highest degree earned by math teacher: Master's or above | -0.10 | 0.11 | -0.92 | 0.36 | 0.90 |

Table 4-10. Continued

| Parameter | Estimate | Std Error | t for H0 | Pr > \|t\| | Estimated odds ratio |
|---|---|---|---|---|---|
| percentage of student body receiving free/reduced-price lunch at high school | 0.01 | 0.002 | 2.54 | 0.01 | 1.01 |
| total cost of college attendance | -0.00001 | 0.00001 | -1.77 | 0.08 | 0.999 |
| chose college for cost | -0.003 | 0.11 | -0.03 | 0.98 | 1.00 |
| institutional selectivity: inclusive | -0.14 | 0.27 | -0.51 | 0.61 | 0.87 |
| institutional selectivity: moderately selective | -0.29 | 0.24 | -1.24 | 0.22 | 0.75 |
| institutional selectivity: highly selective | -0.56 | 0.25 | -2.24 | 0.03 | 0.57 |
| Graduate enrollment in STEM fields | 0.0002 | 0.00004 | 4.64 | <.0001 | 1.0002 |
| highest degree in STEM fields: Master's | -0.46 | 0.16 | -2.8 | 0.01 | 0.63 |
| highest degree in STEM fields: Doctor's, professional and others | 0.06 | 0.14 | 0.44 | 0.66 | 1.06 |
| Interaction: family SES by SAT math score | 0.002 | 0.0007 | 3.36 | 0.001 | 1.002 |
| Interaction: family SES by Black | 0.57 | 0.23 | 2.52 | 0.01 | 1.76 |
| Interaction: family SES by highest degree in STEM fields (Master's) | 0.45 | 0.18 | 2.43 | 0.02 | 1.56 |
| Interaction: family SES by female | 0.24 | 0.14 | 1.72 | 0.09 | 1.27 |

was the consistent negative correlation between one's high school's SES level and his/her probability of STEM enrollment.  Since the SES level of one's high school is likely to be positively related to his/her family SES, the negative correlation between high school SES and STEM enrollment suggests that family SES, although not significant by itself, might still play some role in student's major choice.  I tested the interaction between family SES and gender, being Black, often receiving privileges for good grades, most recent SAT math score, and institution's level of STEM majors.  The interaction between family SES and often receiving privileges for good grades was insignificant and deleted from the model.

Table 4-10 shows the analysis results with significant interaction terms. After adding the interaction terms, school SES is still negatively related to STEM enrollment likelihood (p-value=0.01, estimated odds ratio=1.01). The negative correlation between attending highly selective institution and probability of STEM enrollment (p-value=0.03, estimated odds ratio=0.57) as well as the positive correlation between graduate enrollment in STEM fields and probability of STEM enrollment (p-value<0.0001, estimated odds ratio=1.0002) remain largely unchanged from the analyses without the interaction terms. Noticeably, total cost of college attendance is negatively related to STEM enrollment probability (p-value=0.08, estimated odds ratio=0.999). This suggests that other factors being equal, students who attend more expensive institutions have lower likelihood of choosing STEM majors.

Family SES and SAT math score interact in correlation with STEM enrollment probability (p=0.001). The estimate of the interaction term is positive (0.002), suggesting that the correlation between SAT match score and STEM enrollment probability increases when family SES increases. Family SES interacts with being Black (p=0.01). The positive estimate (0.57) suggests that the stronger preference for STEM majors of Black students compared to white students increases when family SES increases. Similarly, family SES interacts with institution's highest level of STEM degree (Master's) (p=0.02). The positive estimate (0.45) suggests that the gap in the probability of choosing STEM major between students at Master's institutions and at Bachelor's institutions is smaller when family SES increases. Finally, family SES also interacts with gender (p=0.09). The estimate is positive (0.24) and suggests that the gap between female and male students in preference for STEM major is smaller for students with higher family SES.

After determining the interaction of family SES and various independent variables, I tested the significance of the simple slopes for the variables that enter the interaction terms. To do so, I selected several values for the continuous mediator variable(s). Specifically, I selected values at two standard deviations and one standard deviation above and below the mean as well as the mean for family SES and most recent SAT math score. To test the simple slopes for gender, race (Black), highest STEM level offered by institution (Master's), and SAT math score, I selected five values of family SES. To test the simple slopes for family SES, I selected five values for SAT math score while controlling the categorical variables at various combinations. Table 4-11 shows the simple slope estimates for the variables that enter interaction terms except for family SES.

As shown in the table, at all levels of family SES, the correlation between gender and STEM enrollment is significantly negative. However, with the increase of family SES, the negative correlation becomes weaker. For students whose family SES is at the bottom of the spectrum (two standard deviations below the mean), female students' probability of choosing STEM majors is about 25% of that for male students. On the other hand, for students whose family SES is at the top of the spectrum (two standard deviations above the mean), female students' probability of choosing STEM majors is about 50% of that for male students.

Table 4-11. Test for simple slopes for gender, race (Black), highest STEM level offered by institution (Master's), and SAT math score

| Simple slope | Level of moderator variable: family SES | Estimate | Std Error | t for H0 | Pr > \|t\| | Estimated odds ratio |
|---|---|---|---|---|---|---|
| Female | 2 SD below mean | -1.37 | 0.21 | -6.49 | <.0001 | 0.254 |
| | 1 SD below mean | -1.21 | 0.13 | -9.11 | <.0001 | 0.298 |
| | mean | -1.04 | 0.09 | -11.16 | <.0001 | 0.353 |
| | 1 SD above mean | -0.88 | 0.13 | -6.51 | <.0001 | 0.415 |
| | 2 SD above mean | -0.71 | 0.21 | -3.33 | 0.001 | 0.492 |
| Black | 2 SD below mean | -0.08 | 0.32 | -0.25 | 0.8 | 0.923 |
| | 1 SD below mean | 0.31 | 0.21 | 1.45 | 0.15 | 1.363 |
| | mean | 0.7 | 0.19 | 3.66 | 0.0003 | 2.014 |
| | 1 SD above mean | 1.09 | 0.28 | 3.96 | <.0001 | 2.974 |
| | 2 SD above mean | 1.48 | 0.4 | 3.67 | 0.0003 | 4.393 |
| Highest STEM level: Master's | 2 SD below mean | -0.89 | 0.28 | -3.16 | 0.002 | 0.411 |
| | 1 SD below mean | -0.58 | 0.19 | -3.1 | 0.002 | 0.560 |
| | mean | -0.27 | 0.15 | -1.78 | 0.07 | 0.763 |
| | 1 SD above mean | 0.03 | 0.21 | 0.16 | 0.87 | 1.030 |
| | 2 SD above mean | 0.34 | 0.31 | 1.1 | 0.27 | 1.405 |
| SAT math score | 2 SD below mean | 0.002 | 0.001 | 1.58 | 0.12 | 1.002 |
| | 1 SD below mean | 0.004 | 0.001 | 3.91 | 0.0002 | 1.004 |
| | mean | 0.005 | 0.001 | 6.73 | <.0001 | 1.005 |
| | 1 SD above mean | 0.007 | 0.001 | 7.51 | <.0001 | 1.007 |
| | 2 SD above mean | 0.009 | 0.001 | 6.85 | <.0001 | 1.009 |

For Black students, when family SES is below the mean level of family SES, their probability of choosing STEM is not significantly different from that for white students. However, for students whose family SES is at or above the mean level, Black students have higher likelihood of enrolling in STEM majors than white students. This advantage increases as family SES increases. When family SES is at the mean, Black students are about twice as likely as white students to choose STEM majors (estimated odds ratio=2.01). When family SES is one standard deviation above the mean, Black students are almost three times as likely as white students to choose STEM majors (estimated odds ratio=2.97). When family SES is at the top of the spectrum (two standard deviations above the mean), Black students are more than four times as likely as white students to choose STEM majors (estimated odds ratio=4.4).

For students whose family SES is one or two standard deviations above the mean, the level of highest degree in STEM fields offered by institution does not correlate significantly with students' likelihood of choosing STEM majors. However, for students whose family SES is at the mean or below the mean, the association between enrolling in an institution where Master's degree is the highest STEM degree conferred and one's likelihood of choosing STEM major is significantly negative. Moreover, such negative correlation becomes stronger with the decrease of family SES. For students enrolling in Master's degree conferring institution, those whose family SES is at the mean is about 76% as likely to choose STEM majors as students who enroll in institutions where Bachelor's degree is the highest STEM degree. When family SES decreases to one standard deviation or two standard deviations below the mean, this percentage decreases to 56% or 41%, respectively.

When examining the correlation between SAT math score and STEM enrollment likelihood as moderated by family SES, it can be seen that except for students whose family SES is at the bottom of the spectrum (two standard deviations below the mean), SAT math score is positively related to STEM enrollment. Such positive correlation becomes stronger with the increase of family SES. Specifically, when SAT math score increases by one, for students whose family SES is one standard deviation below the mean, at the mean, one standard deviation above the mean, and two standard deviations above the mean, the probability of STEM enrollment increases by 0.4%, 0.5%, 0.7%, and 0.9%, respectively. For students from the lowest SES families, however, SAT math score is not statistically significantly correlated to their likelihood of choosing STEM majors, although the p-value (0.12) does approach significance at the .10 level and the estimate is positive.

Table 4-12. Test for simple slopes for family SES with SAT math score as moderator variable: female

| Level of moderator variable: SAT math score | | Black female, Master's | Non-Black female, Master's | Black female, non-Master's | non-Black female, non-Master's |
|---|---|---|---|---|---|
| 2 standard deviations below the mean | Estimate | 0.3 | -0.27 | -0.15 | -0.71 |
| | p-value | 0.25 | 0.26 | 0.52 | 0.0008 |
| | Estimated odds ratio | 1.35 | 0.76 | 0.86 | 0.49 |
| 1 standard deviation below the mean | Estimate | 0.56 | -0.01 | 0.11 | -0.46 |
| | p-value | 0.03 | 0.96 | 0.6 | 0.004 |
| | Estimated odds ratio | 1.75 | 0.99 | 1.12 | 0.63 |
| Mean | Estimate | 0.81 | 0.24 | 0.36 | -0.21 |
| | p-value | 0.003 | 0.21 | 0.09 | 0.12 |
| | Estimated odds ratio | 2.25 | 1.27 | 1.43 | 0.81 |
| 1 standard deviation above the mean | Estimate | 1.06 | 0.5 | 0.62 | 0.05 |
| | p-value | 0.0005 | 0.02 | 0.01 | 0.71 |
| | Estimated odds ratio | 2.89 | 1.65 | 1.86 | 1.05 |
| 2 standard deviations above the mean | Estimate | 1.32 | 0.75 | 0.87 | 0.31 |
| | p-value | 0.0002 | 0.003 | 0.003 | 0.1 |
| | Estimated odds ratio | 3.74 | 2.12 | 2.39 | 1.36 |

Since family SES enters more than one interaction terms, simple slopes were tested by selecting various values for SAT math score and holding categorical variables at different combinations. Table 4-12 shows the simple slope estimates for family SES for female. For female students whose SAT math scores are one or two standard deviation(s) above the mean, family SES is positively related to STEM enrollment for all subgroups except for non-Black female students attending institutions where the highest STEM degree is not Master's degree. The higher the SAT math score, the stronger is the positive correlation between family SES and STEM enrollment. For example, for students whose SAT math score is at the top of the spectrum (two standard deviations above the mean), a one point increase in family SES is associated with a probability of STEM enrollment 3.7 times as large for Black female students attending Master's institutions. The same value for students whose SAT math score is one standard deviation above the mean is 2.89.

For Black female students whose SAT math score is at the mean, family SES is also positively correlated to STEM enrollment probability. The correlation is stronger for those attending Master's institutions. For female students whose SAT math score is below the mean, the correlation between family SES and STEM enrollment dramatically changes. For non-Black female students attending non-Master's institutions, family SES is negatively associated with STEM enrollment probability (estimate= -0.46, p-value=0.004). This suggests that with one point increase in family SES, the probability of choosing STEM major for this subgroup decreases to about 63% of the original value. The same trend holds for students from this subgroup whose SAT math scores are even lower (two standard deviations below the mean) and the negative correlation is even stronger (estimated odds ratio=0.49). However, for Black female students attending Master's institutions, when SAT math score is one standard deviation below the mean, the correlation between family SES and STEM enrollment is still positive (p-value=0.03, estimated odds ratio=1.75). For all other subgroups, when SAT math score

Table 4-13. Test for simple slopes for family SES with SAT math score as moderator variable: male

| Level of moderator variable: SAT math score | | Black male, Master's | Non-Black male, Master's | Black male, non-Master's | Non-Black male, non-Master's |
|---|---|---|---|---|---|
| 2 standard deviations below the mean | Estimate | 0.06 | -0.5 | -0.38 | -0.95 |
| | p-value | 0.8 | 0.03 | 0.09 | <.0001 |
| | Estimated odds ratio | 1.06 | 0.61 | 0.68 | 0.39 |
| 1 standard deviation below the mean | Estimate | 0.32 | -0.25 | -0.13 | -0.69 |
| | p-value | 0.19 | 0.18 | 0.53 | <.0001 |
| | Estimated odds ratio | 1.38 | 0.78 | 0.88 | 0.50 |
| Mean | Estimate | 0.57 | 0.006 | 0.13 | -0.44 |
| | p-value | 0.02 | 0.97 | 0.54 | 0.0002 |
| | Estimated odds ratio | 1.77 | 1.01 | 1.14 | 0.64 |
| 1 standard deviation above the mean | Estimate | 0.83 | 0.26 | 0.38 | -0.19 |
| | p-value | 0.004 | 0.16 | 0.11 | 0.13 |
| | Estimated odds ratio | 2.29 | 1.30 | 1.46 | 0.83 |
| 2 standard deviations above the mean | Estimate | 1.08 | 0.52 | 0.64 | 0.07 |
| | p-value | 0.001 | 0.02 | 0.03 | 0.68 |
| | Estimated odds ratio | 2.94 | 1.68 | 1.90 | 1.07 |

is below the mean, family SES does not play a role in the probability of STEM enrollment.

Table 4-13 shows the simple slope estimates for family SES for male. For male students, when SAT math score is very high (two standard deviations above the mean), family SES is positively related to STEM enrollment except for non-Black students attending non-Master's institutions. When SAT math score is one standard deviation above the mean, the positive association only holds for Black male students attending Master's institutions. When SAT math score is at the mean, the positive association still holds for this subgroup. However, for another subgroup, the correlation becomes negative. For non-Black male students attending non-Master's institutions, when SAT math score is at the mean, family SES is negatively correlated to STEM enrollment (p-value=0.0002, estimated odds ratio=0.64). Such negative correlation also holds for this subgroup when SAT math score is below the mean. When SAT math score is very low (two standard deviations below the mean), the negative correlation holds for all male students except for Black male students attending Master's institutions. For both the positive and negative correlations, the more extreme the SAT math score, the stronger is the correlation between family SES and STEM enrollment probability.

Table 4-14. Pseudo *R*-squared (Cox-Snell's) for four logistic regression models

| Model | Cox-Snell's R-squared |
|---|---|
| Block 1: individual context variables | 0.08 |
| Block 1 and 2: individual and pre-college context variables | 0.13 |
| Block 1- 3: individual, pre-college, and college context variables | 0.14 |
| Block 1 - 4: individual, pre-college, college context variables and interaction terms | 0.15 |

Table 4-14 shows the Cox-Snell's R-squared for the four logistic regression models with block entry. As can be seen, the Cox-Snell's *R*-squared increases with the increase of number of independent variables entered in the model. Pseudo *R*-squared of logistic regression, such as the Cox-Snell's *R*-squared reported here, measures the improvement from the null model with no predictors to fitting the model with certain independent variables, rather than the variance explained by the model. Although the values of the *R*-squared are small, the constant increase suggests that entering additional predicators and interaction terms did improve the model.

## Summary of Results

This chapter presented results from the preliminary and advanced analyses. Descriptive statistics, chi-squared tests, and independent sample t-tests were used to describe the analysis sample and examine group differences between STEM and non-STEM students on independent variables. Results show that STEM and non-STEM students differ on factors including family SES, gender, race, parental expectation, native language, whether receive special privileges for good grades, math preparation level, selectivity of institution, STEM offering scale and level at institution, as well as total cost of college attendance. On average, STEM students have higher family SES, higher math preparation level, and attend colleges with larger STEM enrollment and lower cost. STEM students receive special privileges for good grades less frequently, more often choose college for financial concerns, and have higher educational expectations from both parents and themselves.

Results from logistic regression analyses with block entry of independent variables show that gender and whether given special privileges for good grades are consistently correlated to STEM enrollment probability, with female and those who often receive such privileges disadvantaged in terms of choosing STEM majors. Having a native language other than English is positively correlated to STEM enrollment without controlling for pre-college and college context variables. After controlling for such factors, the correlation between native language and STEM enrollment disappeared. After controlling for pre-college variables, race (being Black) is positively correlated to STEM enrollment. Not surprisingly, SAT math score is positively related to choosing STEM majors. Interestingly, although independent t-test show that STEM and non-STEM students do not differ significantly on the SES level of the high school they attend (as measured by the percentage of student body receiving free/reduced-price lunch), logistic regression analyses show consistent significant negative correlation between high school SES and STEM enrollment. Institutional selectivity is negatively correlated to STEM enrollment, while STEM major enrollment scale on the graduate level is positively correlated to choosing STEM major. Enrolling in Master's institution (institutions where the highest degree conferred in STEM fields is Master's degree) is negatively correlated to the probability of choosing STEM majors. While family SES itself is not statistically significantly correlated with STEM enrollment, it does interact with several factors including gender, race, STEM degree level, and math preparation. After entering interaction terms, the total cost of college attendance is negatively related to STEM enrollment. In the next chapter, I interpret these findings in more detail, answer the research questions, compare the findings to existing research literature, and discuss implications for practice and future research.

# CHAPTER 5
# DISCUSSION AND CONCLUSION

In this chapter, I discuss the findings related to the research questions and their congruence with previous research findings. Then I describe the implications of the findings for practice and future research, followed by the conclusion of this study.

## Discussion of Findings

In the previous chapter, the analyses results were presented and described. In this subsection, I discuss the findings in detail by relating them to the research questions, the theoretical framework, and existing research literature. I start with a review of the purpose of the study, the theoretical framework, the research questions, and the proposed hypotheses.

The purpose of this study was to examine college students' enrollment pattern in STEM majors with a focus on students' family SES. I examined whether students' enrollment in STEM majors is systematically related to their family SES and if so, what the direction and magnitude of such association is. The following research questions were investigated:

- Research question 1: Is students' family SES related to their decision of whether to enroll in a STEM major in college?
- Research question 2: Does the enrollment decision in STEM fields vary for students with different college investment levels?
- Research question 3: Does the enrollment decision in STEM fields vary at institutions with different scales and levels of STEM major offerings?

To answer these questions, I adopted the theories of human capital and rational choice. Students were assumed to be rational actors in their decision of major choice and it was assumed that they have weighed the potential gains of certain college majors against the monetary and non-monetary investments they and their families make in their own human capital. While students are confined in their individual and environmental contexts when they make educational decisions, economic factors and family SES were hypothesized to play a role in their major choice decisions. Figure 5-1 shows the hypothesized interaction of family SES and human capital investment through higher education under the assumption of rational actors. Based on the theoretical framework, which mainly takes an economic perspective, the following hypotheses were proposed:

- Hypothesis 1: College students' family SES is negatively correlated to enrolling in STEM majors, controlling for individual, pre-college, and college context factors.
- Hypothesis 2: Students' college investment level is positively related to enrolling in STEM majors.
- Hypothesis 3: The scale and level of STEM major offerings at an institution are correlated to students' decision of STEM major enrollment.

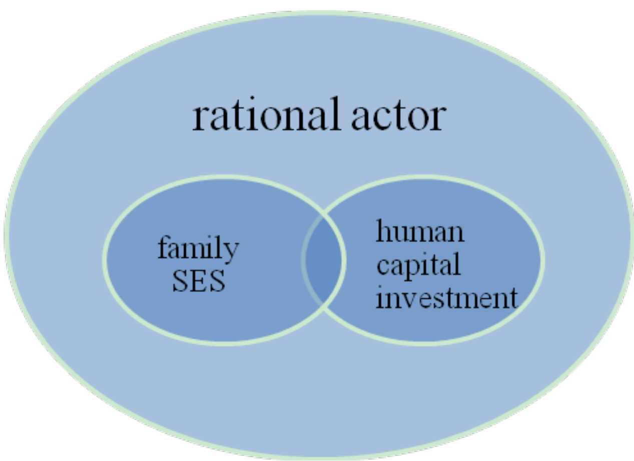



Figure 5-1. Hypothesized interaction between family SES and human capital investment

In the following subsections, I discuss whether the analyses findings support these hypotheses and whether they are consistent with existing research literature.

## Family SES and STEM Enrollment

When controlling for individual, pre-college, and college context factors, I hypothesized that students' family SES would be negatively correlated to enrolling in STEM majors. Logistic regression analyses results show that when controlling for individual, pre-college, and college context variables, the estimate of family SES is negative (-0.11). However, the p-value is insignificant (0.16), suggesting that family SES by itself is not significantly correlated with STEM enrollment for the whole sample. Further analyses show that family SES interacts with several variables including gender, race (Black), highest level of STEM degree at institution (Master's), and SAT math score.

The examination of the simple slope for family SES show interesting findings. Although family SES is not significant for the whole sample, the results show that it is significant for several subgroups and the direction of the correlation is different for different subgroups. For some students whose SAT math score is low, the relationship between family SES and STEM enrollment is negative, as hypothesized. For example, for non-Black students with low SAT math score who attend institutions where the highest level of STEM degree is either Bachelor's, doctoral, or professional, family SES is negatively related to STEM enrollment. When SAT math score is very low (two standard deviations below the mean), for all male students except Black males attending Master's degree institutions, family SES is negatively related to STEM enrollment. On the contrary, for students with high SAT math score, family SES is positively related to STEM enrollment, which is the opposite of the hypothesis. For example, when SAT math score is very high (two standard deviations above the mean), family SES is positively related to STEM enrollment for all students except non-Black students attending non-Master's institutions. For female students, such association holds when SAT math score is one standard deviation above the mean. Even when SAT math score is only at the mean, Black female students' family SES is still positively related to their STEM enrollment.

While the trend does not hold for every subgroup of students, the results show that for most students, when SAT math score falls below the mean, significant correlation between family SES and STEM enrollment, if any, is negative. When SAT math score is at the mean or above the mean, significant correlation between family SES and STEM enrollment, if any, is positive. The only exception is for Black female students attending Master's institutions. Even when SAT math score is one standard deviation below the mean, family SES is still positively related to STEM enrollment. These findings suggest that family SES is related to STEM enrollment only for some students. Among the students whose family SES does relate to STEM enrollment, the direction of the correlation is negative mainly for those with low math preparation level and positive mainly for those with average or high math preparation level. Regardless of the direction of the correlation, the more extreme the SAT math score, the stronger the association between family SES and STEM enrollment.

Ma (2009) concludes that students from lower SES families tend to choose major fields that yield higher financial rewards upon college graduation, such as technical and life/health sciences. Findings from this study show that negative correlation between family SES and STEM enrollment does exist for some students. However, it is necessary to examine this correlation more closely before concluding that lower SES students prefer STEM majors more than their higher SES peers and that the assumptions of this study are supported by empirical evidence. First, it should be noticed that the negative correlation exists only for some subgroups of the students rather than the whole sample. For example, for Black students attending Master's institutions, all significant correlations between family SES and STEM enrollment are positive. For female students, negative correlation only exists for non-Black students attending non-Master's institutions.

Second, it should be noticed that lower SES students are more likely to choose STEM majors than higher SES students only when the math preparation is poor. When math preparation is average or high, all correlations are positive except for one. In other words, for some students (for example, non-Black students attending non-Master's institutions) who are poor at math, those from higher SES families are less likely to enroll in STEM majors while those from lower SES families are more likely to do so. Also, for some students who are average or good at math, those from higher SES families are more likely to enroll in STEM majors while those from lower SES families are less likely to do so. If the assumptions of this study accurately explain students' major choice, then empirical evidence should show that negative correlation between family SES and STEM enrollment exists for the whole sample regardless of the level of math preparation. The opposite directions of the correlations for students with different math preparation suggest that students' behavior is not in accordance with the hypotheses.

Why does this happen? When examining the correlation between math preparation level and STEM education in college, it can be seen that math preparation is one of the most important predictors of STEM enrollment and retention. Students with higher math preparation level have higher chance of succeeding in STEM majors while those with poor math preparation are more likely to leave STEM fields (Seymour & Hewitt, 1997). Choosing a major that matches one's academic preparation will increase one's probability of succeeding in college. Therefore, an informed decision regarding STEM enrollment should be based on one's math preparation among other factors. In other words, if a student chooses STEM major despite very low math preparation level, it should be questioned whether his or her decision is a sound one in terms of the chance to succeed.

Knowing that STEM enrollment decision should be based partly on one's math achievement level, the face value of the negative correlations detected from the analyses is questioned. Is the negative association the result of students' economic and human capital concerns, or is it rather the result of uninformed decision making? If the former holds, then the positive correlation between family SES and STEM enrollment among high math achievement students cannot be explained. The latter, on the other hand, is in accordance with the observed trends. Higher SES students know better when to choose STEM majors (when their math level is high) and when to avoid them (when math level is low), while lower SES students do not. Literature has shown that family SES influences students' navigation through the higher education system and their chance to succeed in college (McDonough, 1997). In terms of STEM enrollment, the influence of family SES on students' knowledge of the system and skills of information collection and decision making seem to affect students' STEM decision as well. One possible explanation for the observed correlations is that students from lower SES families lack knowledge about STEM majors, about the demanding nature of study in STEM, and the potential career perspectives in STEM fields. As a result, lower SES students may choose STEM majors without measuring their chance of success, or ignore STEM majors without even knowing what STEM majors have to offer upon graduation. In sum, the results appear to be partially consistent with existing findings and the first hypothesis seems to be partially supported. However, after examining the findings closer, it can be seen that the first hypothesis is in fact not supported and the results are inconsistent with existing findings (Ma, 2009).

**College Investment Level and STEM Enrollment**

The second hypothesis stated that students' college investment level is positively related to STEM enrollment. College investment level was measured by the total cost of attendance for each student. The reasoning behind this hypothesis was again based on the framework of human capital investment. Since students were assumed to be rational actors, it was assumed that the higher the cost of college attendance, the more students will take into consideration the potential financial reward of college education and as a result, prefer study areas with better career perspectives such as STEM majors. Results show that the total cost of college attendance is, however, negatively correlated to STEM enrollment probability. This suggests that the higher the cost of attending college, the lower the probability of choosing STEM majors.

Research has revealed that the expected earning is significantly correlated to students' major choice in college (Montmarquette, Cannings, & Mahseredjian, 2002). However, not much research has examined the association between college cost and major choice. Shin and Milton (2008) conclude that students' enrollment in college is correlated to tuition level and the correlation differs by discipline. Their findings show that tuition level is negatively correlated to enrollment in physics, biology, and business and tuition level is not correlated to enrollment in engineering. This study's finding of negative correlation between total cost and STEM enrollment is partly inconsistent with Shin and Milton's (2008) findings. However, it is noteworthy that in Shin and Milton's (2008) study, the analyses focus on the institutional level rather than on the individual level. As a result, individual characteristics are not controlled in their study. St. John (1994b) concludes that debt burden is not significantly associated with major choice in college, implying that college investment that exceeds students' financial means does not influence the choice of study field in college. In other words, paying a price that is not easily affordable for college does not significantly influence students' decision about college major. The finding of negative correlation from this study is again inconsistent with the finding by St. John (1994b).

While it is not clear why college cost is negatively correlated with STEM enrollment, we can see that the second hypothesis is not supported by the findings. One possible explanation is that the measurement of college investment level is not ideal in this study. Due to the lack of continuous variable of family income and the high missing rate of financial aid and debt variables, it is impossible to calculate college investment level as the ratio of actual cost of college to one's family income. While such calculation would have revealed more information about the difficulty level of paying for college, the measurement used in this study only reveals the sticker price of college. This limitation may have masked the correlation between college investment and STEM enrollment.

Given the above consideration, perhaps the main reason for the disagreement between the second hypothesis and the finding is that the assumptions of this study are not supported by the findings. If economic considerations are not the main factors influencing informed decision making regarding STEM enrollment, the proposed correlation between college investment and STEM enrollment will not hold either. As a result, it is not surprising to see that college cost is not positively related to STEM enrollment probability. In other words, the first two hypotheses are based on the same reasoning, which assumes that students make informed decisions of college major by prioritizing economic considerations. The disagreement of the second hypotheses and the finding reaffirms that the proposed assumptions do not hold.

**STEM Offering and STEM Enrollment**

The third hypothesis stated that the scale and level of STEM major offerings at an institution are correlated to students' decision of STEM enrollment. Results show that graduate enrollment in STEM majors is positively correlated with STEM enrollment probability. The level of the highest degree conferred at an institution in STEM (Master's) interacts with family SES in its correlation with STEM enrollment. While the hypothesis appears to be supported by the findings, the interpretation of the observed correlations is not obvious. One possible explanation of the correlation between graduate STEM enrollment and undergraduate STEM enrollment probability is the increased exposure to STEM fields. Students at institutions where graduate STEM enrollment is large may be exposed more to STEM fields through interaction with STEM faculty members and students. They may also have access to more information about STEM fields through campus news, personal contact, and/or academic counseling services. Institutions with large graduate enrollment in STEM fields may also have campus culture of pursuing STEM studies and good academic reputation of STEM fields. Being exposed to people and news in STEM fields may help students gain better understanding of STEM programs and career prospective.

The competing explanation for this correlation is that students who are more likely to enroll in STEM majors choose to enroll at institutions with large STEM offerings. Research has shown that many students choose a certain college because they find it to be a good place to pursue the major field they are interested in (Cabrera & La Nasa, 2000; Hossler, Schmit, & Vesper, 1999; Maltese & Tai, 2011; Martin & Dixon, 1991). Since this study is correlational rather than causal, a simple interpretation of the correlation between graduate STEM enrollment and undergraduate STEM enrollment probability cannot be reached. A causal research design or a qualitative study would be more likely to shed light on this aspect.

Little research has been conducted on the correlation between STEM offering level of institution and students' probability of STEM enrollment. Results of this study show that when enrolling at institutions where Master's degree is the highest STEM degree conferred, students from lower SES families are less likely to choose STEM majors compared to those enrolling at institutions where Bachelor's degree is the highest STEM degree conferred. This may be the result of characteristics of Master's institutions, or the result of choosing college for major. In other words, students from lower SES families may tend to choose Master's institutions for non-STEM majors. Again, causal research design or qualitative study on this topic may reveal the mechanism behind the observed decision making behaviors.

## Predictors of STEM Enrollment and Insignificant Variables

### Predictors

In addition to the main findings discussed above, the analyses results also revealed several other predictors of STEM enrollment. Percentage of free/reduced-price lunch program participation at the high school one attended is one of the variables that are significantly correlated to STEM enrollment probability. The positive correlation suggests that other factors being held equal, students whose high schools have higher percentage of students receiving free/reduced-price lunch are more likely to choose STEM majors in college. Percentage of free/reduced-price lunch program participation is an important measurement of school's SES composition, which is defined as the aggregate of the individual students' family SES (Cowan et al., 2012). This finding suggests that other factors being equal, students who come from lower SES high schools are more likely to choose STEM major in college than those who attended higher SES high schools.

In the American K-12 education system, students typically attend schools in their neighborhood while schools are largely funded locally (U.S. Department of Education, 2005). Consequently, schools in lower SES neighborhood tend to be underfunded and their educational quality tends to be lower than schools in more affluent neighborhoods (Cunningham & Sanzo, 2002). In this sense, the quality of the schools students attend depend on the neighborhood SES. In general, the lower the neighborhood SES, the lower is the quality of its schools (Mackenzie, 2010). Low SES students tend to attend high schools in low SES neighborhoods, receive lower quality teaching and student services, and have fewer chance of being successful academically (Cowan et al., 2012; Darling-Hammond, 2004).

The positive correlation between percentage of free/reduced-price lunch participation at high school and STEM enrollment suggests that students from disadvantaged educational background tend to prefer STEM majors more than their counterparts from advantaged educational background. One possible explanation is that for students who attend lower SES high schools to achieve the same academic level as their counterparts who attend higher SES high schools, more efforts from the students are needed in order to overcome the disadvantage of lower quality teaching and other educational components (Wyner, Bridgeland, & DiIulio, 2007). Therefore, students who do achieve the same academic preparation level despite the disadvantage of attending lower quality high schools may have compensated for the disadvantage through desirable personal characteristics. Students' compensatory efforts might have been the result of high motivation for academic success, good study skills and/or cognitive skills, high self-efficacy in study, and good self-regulation. These factors have been identified as important predictors of better academic performance (DeBerard, Spielmans, & Julka, 2004; House, 2000; Kitsantas, Winsler, & Huie, 2008; Norvilitis & Reid, 2012; Parker et al., 2004). Students who possess these characteristics may be more confident in study and more willing to take academic challenges, such as STEM majors. They may be less concerned about the demanding nature of these majors and be able to choose majors that best meet their educational needs.

It is noteworthy that the percentage of free/reduced-price lunch participation at high school is consistently significantly correlated to STEM enrollment, even without controlling for college context variables. This suggests that the factor(s) behind high school SES that are related to higher likelihood of STEM enrollment are relatively context independent. Research has pointed out that school SES level and school SES composition represented by the percentage of students across family SES levels have significant influence on students' academic achievement and psychological development (Crosnoe, 2009; Rumberger & Palardy, 2005). The impact of school SES is argued to be as much as the impact of family SES and persistent across students' family SES levels and school control (Rumberger & Palardy, 2005). While less is known about the correlation between school SES and students' major choice in college, the finding of this study suggests that such correlation does exist and is independent of the characteristics of the college students attend. Further research is needed to reveal the mechanism underlying the correlation. It is encouraging to see that STEM fields are not losing talents from disadvantaged educational background such as lower SES high schools.

Another variable that is significantly correlated to STEM enrollment is high institutional selectivity of the college students attend. Compared to students enrolling in institutions without a classified selectivity, students enrolling in highly selective institutions are less likely to enroll in STEM majors. It is noteworthy that students enrolling in inclusive and moderately selective institutions do not differ significantly from those enrolling in institutions without a classified selectivity in the likelihood of STEM enrollment. One plausible explanation for the lower likelihood of STEM enrollment for students from highly selective institutions is that such institutions focus more on liberal arts education for undergraduate students, such as Harvard University or liberal arts institutions such as Lawrence University and Beloit College. Highly selective institutions tend to emphasize the acquiring of general knowledge and skills more often than training students to acquire marketable skills (Deresiewicz, 2008). As a result, the institutional culture may emphasize that undergraduate students explore their interests, develop critical thinking abilities and leadership skills, and prepare for higher level education such as graduate school or professional school. This may be related to lower preference for STEM majors, which are oftentimes seen as applied training (Ma, 2009).

Another plausible explanation is that students who choose to apply for and enroll in highly selective institutions generally prefer STEM fields less. Therefore, it is not the characteristics of the highly selective institutions that influence students' major choice, but that the students come to the institutions predetermined about the majors they are interested in. Again, the significant correlation between institution selectivity and STEM enrollment likelihood does not reveal why such correlation exists. Causal research design or qualitative study is needed to find out why STEM majors are less attractive to students at highly selective institutions.

Interestingly, compared to students who never or rarely receive special privileges at home for good grades, those who often receive special privileges from parents for good grades are significantly less likely to choose STEM majors in college. This result was consistent across models, even without controlling for academic preparation. Research on parent-child interaction shows that when parents use privileges or material rewards to encourage children to perform better academically, children may develop extrinsic motivational orientations and intrinsic motivation for study may be undermined (Cameron & Pierce, 1994; Deci, Koestner, & Ryan, 1999). In other words, when children are rewarded for good grades by material things or privileges, the motivation for performing well in school is supported by the desire for the pending reward from parents rather than by the satisfaction from learning and achieving itself or by one's own educational expectations (Davis, Winsler, & Middleton, 2006; Greenberger, Lessard, Chen, & Farruggia, 2008). Thus children who often receive privilege or material rewards tend to lose interest in study itself and avoid arduous study if possible. When taking into account the demanding nature of the study in STEM fields, it is not surprising that students who are often given privileges by parents for good grades tend to avoid STEM fields once they are in college.

Race, gender, and math achievement are among the most important predictors of STEM enrollment in college (Peard, 2004; Rask, 2010; Riegle-Crumb & King, 2010; Trusty, 2002). The results of this study also show that these three factors consistently predict STEM decision making. Moreover, all of these factors interact with family SES in their correlation with STEM enrollment. While SAT math score is positively correlated with STEM enrollment, the significant effect does not exist for students from the lowest SES families (two standard deviations below the mean). That math achievement does not predict STEM enrollment for lowest SES students suggests that these students make STEM decisions differently than other students in terms of math level. This finding is consistent with the discussion that lower SES students do not interpret their academic achievement in ways that align their abilities with college education opportunities. Qualitative analyses might help to shed light on the reasons for these observations.

Females are significantly less represented in STEM fields than male (Beede, Julian, Langdon, McKittrick, Khan, & Doms, 2011; Espinosa, 2011). Researchers and policy makers have long been making efforts to attract more female students into STEM fields and to keep them in those fields (Hill, Corbett, & St. Rose, 2010). It is not surprising to see that regardless of their family SES, female students are always less likely than male students to enroll in STEM fields. However, it is noteworthy that as family SES increases, the gender gap becomes smaller. In other words, although females are generally underrepresented in STEM fields, a higher SES family helps to make female students less disadvantaged.

Race is another widely studied factor in terms of STEM education in college (Anderson & Kim, 2006). Results of this study show that Black students are more likely to choose STEM majors in college than White students. Researchers have long pointed out that minority students, except for Asian students, are underrepresented in STEM fields (Cole & Espinoza, 2008; Huang, Taddese, Walter, & Peng, 2000). This study show that despite the underrepresentation, Black students are in fact more willing to pursue STEM studies than white students. This finding is consistent with previous research finding that Black students are more likely to pursue higher education than white students once family SES is accounted for (Hauser, 1993). While this is encouraging, it should be noticed that this trend only holds for Black students from families of at least average SES. For Black students from lower than average SES families, the likelihood of choosing STEM majors is not significantly different from that of white students. Again, findings of this study show that higher family SES helps underrepresented students in pursuing STEM studies. It also should be noticed that although the interaction of family SES does not apply to Black students from low SES families, their likelihood of selecting STEM majors is not significantly lower than white students, either.

**Insignificant variables**

While the significant correlations reveal predictors of enrollment in STEM fields, the insignificant variables are no less informative (Rothstein, Sutton, & Borenstein, 2005). Results consistently show that except for Black students, all other racial groups do not differ from white students in the likelihood of STEM enrollment. This is encouraging especially because Hispanic students, who are frequently identified as disadvantaged in the higher education system (Swail, Cabrera, Lee, & Williams, 2005), are not significantly less likely to choose STEM majors in college than white students. The same applies to Black students from low SES families. When the other factors are equal, most racial groups are in fact equally willing to pursue STEM education.

Parental expectation is not significantly correlated to STEM enrollment likelihood and the insignificant results are consistent across models. Research has shown that parental support such as expectation reduces the influence of undesired factors and hence is helpful for students to achieve academic success (Ong, Phinney, & Dennis, 2006). The finding of this study suggests that when other factors are equal, students' preference for STEM majors does not vary with the educational expectations of their parents. This means that STEM recruitment in college could be successful among students who lack high expectations from their parents.

Similarly, the frequency of discussion about course work between students and parents is not correlated to STEM enrollment likelihood and the results are consistent across models. This suggests that when controlling for academic achievement and institutional factors, whether students often discuss school work with parents is not related to later major choice. The insignificance of these two variables suggests that parental support does not play a vital role in STEM enrollment after controlling for academic achievement. This finding should not be interpreted as suggesting that parental support is unimportant in promoting STEM education in college, since the correlation may be masked by academic achievement. The way parents interact with children about school work in fact has important impact on students' STEM preference, as shown by the negative correlation between privilege receiving and STEM enrollment. Qualitative inquiry would be useful in providing a better understanding of how interactions between parents and children impact students' STEM preference.

Students' own educational expectation, cited as a factor that is positively related to educational attainment (Zimmerman, Bandura, & Martinez-Pons, 1992), is not significantly related to STEM enrollment and the result is consistent across models. This is similar to the insignificance of parental expectation, which is also insignificant across models. The finding is consistent with previous findings that students with various academic achievement levels may have similar educational aspirations (Pitre, 2006). The lack of correlation between educational expectation and STEM enrollment suggests that students do not prefer or avoid STEM majors simply because of the highest level of education that they or their parents hope them to achieve. In other words, STEM majors may be attractive for students with various educational aspirations.

Result from the model with only individual context variables shows that compared to non-native English speakers, native English speakers are less likely to choose STEM majors in college. However, after controlling for pre-college context variables, the correlation disappeared. While researchers have argued that students from new immigrant families tend to prefer study fields of technical nature due to the desire for economic security and social mobility (Song & Glick, 2004), the finding from this study shows that students with immigration background are not significantly different from native students in preference for STEM majors. The variable indicating family's resources for study, whether family has more than 50 books, does not correlate to students' STEM enrollment and the result is consistent across models. While educational resources at home have been identified as predictors of children's academic achievement (Mullis, Rathge, & Mullis, 2003), they do not appear to play a role in STEM enrollment preference within the context of this study.

In terms of pre-college context variables, the highest level of math completed in high school is not significantly related to STEM enrollment. The finding may be because that SAT math score is controlled for. Another plausible explanation is that students may not be taking their math preparation level into serious consideration when making STEM decisions. In other words, the level of math courses taken in high school does not predict whether a student is more or less likely to choose STEM major in college. This finding is consistent with the findings of Beecher and Fischer (1999) that high school course type does not predict college academic success. Rather, it is high school GPA and standard test scores that predict the academic performance of college students (Beecher & Fischer, 1999).

High school quality is often cited as an important predictor of student academic achievement and access to and success in college (Berkowitz & Hoekstra, 2011; Fletcher & Tienda, 2010; Pike & Saupe, 2002). Teacher quality is one of the indicators of school quality (Mayer, Mullens, & Moore, 2001). While previous research has shown that high school math teacher credential predicts students' academic performance (Rice, 2003), finding from this study suggests that the highest level of degree earned by math teacher does not predict students' STEM enrollment decision. One possible explanation is that highest degree earned is only one aspect of teacher quality, while teaching experiences, the quality of instructional experiences teachers provide students with, whether teachers are certified in the field in which they teach, and participation in professional development may be more accurate indicators of teaching quality (Mayer, Mullens, & Moore, 2001).

Students' decision about STEM enrollment does not vary with whether they have chosen the college for concerns of cost. This is not surprising given the fact that the assumption of economic concerns being predictor of preference for STEM majors is not supported by the main findings. Whether students see finding steady work as very important or whether students have participated in college counseling programs at high school are unrelated to STEM decision in college. This suggests that college counseling at high schools, if provided, does not have strong impact on students' STEM decisions, implying room for improvement for high school counselors.

**Conceptual Framework Revisited**

The results suggest that the assumptions, which take an economic perspective, do not explain college students' STEM decision making. Does this mean that family SES is not important in terms of STEM enrollment in college? The interaction of family SES with strong predictors of STEM enrollment shows that family SES does matter when it comes to the question of who is pursuing STEM studies in college nowadays. Why do the assumptions not hold? How does family SES influence students' STEM decision making?

The mechanism assumed by this study was a rational action one. It was assumed that students act rationally based on related information, which means that they weigh the potential gains against the cost before making decisions. It was also assumed that economic concerns are primary factors that guide students' college decision making. Combined, it was assumed that students see college education as human capital investment in themselves and that their decision about STEM enrollment is correlated to their financial concerns, which are decided by their family SES.

National data show that most students find earning money to be very important (Pryor, Hurtado, DeAngelo, Blake, & Tran, 2009). This suggests that students have financial concerns and value the importance of financial rewards. Results also show that the most advantaged students, such as those from higher SES families and have high academic achievement, realize the value of STEM studies. Given students' emphasis on financial factors and the recognition of the value of STEM fields, why do the assumptions not hold? It could be that students are in fact not rational actors. Perhaps they do not weigh the gain against the cost, or they do not possess the same information, or both. Another reason could be that while students do have financial concern, it is not the deciding factor in STEM decision making. The fact that lower SES students do not seem to align math achievement with STEM enrollment decisions suggests that they may not possess the information and/or skills necessary to make educational decisions that maximize their opportunity to succeed.

Family SES is a complex construct. The most common components are parents' education, parents' occupation, and family income (Cowan et al., 2012). For students, neighborhood SES and school SES are sometimes combined with family SES to account for the whole living and learning environment (Cowan et al., 2012). Family SES not only measures a family's financial means, but also measures the family's social and cultural resources (Cowan et al., 2012). For lower SES families, social connections and cultural resources are oftentimes scarce (Bradley & Corwyn, 2002). As a result, children from these families may lack educational support in many aspects from family and school when it comes to preparing for college (Swail, 2000; Tornatzky, Cutler, & Lee, 2002).

While the assumptions of this study focused on the aspect of family income, they did not account for parents' educational level and occupation, or the neighborhood SES and school SES. These factors, while correlated to family income, do have distinct impact on students' educational achievement (Cowan et al., 2012; De Graff, De Graaf, & Kraaykamp, 2000). The educational level and occupation of parents, family members, and neighbors may influence students' knowledge and understanding of occupations (Cowan et al., 2012; Dubow, Boxer, & Rowell, 2009; Leppel, Williams, & Waldauer, 2001). The quality of teaching and academic counseling services of the schools students attend is likely to impact their skills of information collection, interpretation of own strengths and weaknesses, and educational decision making (McDonough, 2005). The results of this study show that while family SES matters in STEM decision making, it is not functioning through the economic mechanism. Rather, it may be functioning through the less easily measureable social and cultural resources decided by parents' education and occupation, the neighborhood SES, and school SES.

## Implications

In this section, I discuss the implications of the findings of this study for practice and future research. Although this study is not causal, the findings reveal important correlations between individual, pre-college, and institutional characteristics and STEM enrollment in college. Student decision making is a complex process, which is a result of impacts from all aspects of the living and learning environment. In this sense, STEM decisions are made by all actors in students' lives, including parents, family members, teachers, peers, college administrators, and education policy makers. Promoting STEM enrollment in college is unlikely to be a solo task completed by students themselves.

## Implications for Practice

Findings of this study have several implications for practice both in high school and in college. The finding that lower SES students tend to make STEM decisions that do not align with their academic preparation level suggests that efforts should be made to help these students make decisions that maximize their opportunity to succeed in college. The first recommendation is that parents of all social classes be given guidance on interaction modes with children. The second recommendation is that college recruitment teams should collaborate with high schools in providing lower SES students with more information about STEM majors. The third recommendation suggests that colleges take steps to recruit their lower SES students for STEM majors.

### Guidance for parents

The findings suggest that students who receive special privilege for good grades are less likely to choose STEM majors. Although this issue is specific to the dynamic of family interactions, school educators can in fact play a role in improving the way parents involve in students' academic performance. Researchers have argued that parental involvement is to certain extent shaped by the school context (Rowan-Kenyon, Bell, & Perna, 2008). School teachers could provide parents with suggestions on how to effectively promote students' academic performance and encourage them to strengthen students' intrinsic rather than extrinsic motivation . While many parents expect good performance from their children, they may not understand that rewarding for good grades could lead to undesirable side effects such as reduced intrinsic interest in study (Gneezy, Meier, & Rey-Biel, 2011). Through communication with parents, school teachers could help parents develop better skills of parent children interaction. This is not limited to high school teachers, since good interaction mode between parents and children should be established as early as possible (Spera, 2005).

**Guidance for high school students**

The findings of this study suggest that lower SES students may lack understanding of the nature of STEM majors, STEM career perspectives, and how to prepare themselves for college study in these fields. Collaboration between college recruitment and high school could provide students, especially lower SES students, with information about STEM majors. College knowledge is crucial for students to gain access to higher education (McDonough, 2005). Preparation for college is mainly done in high school, where students develop aspirations, prepare academically, and take steps to apply for college admission (Carnevale & Desrochers, 2003). Providing students with proper college counseling could be a deciding factor for students' pathway to higher education, especially for lower SES students, whose family and living environment may not be able to provide sufficient information and guidance in this aspect (Hossler, Schmit, & Vesper, 1999). Since college counseling service at lower SES high schools tend to be insufficient (McDonough, 2005), outreach efforts made by colleges could be helpful in providing disadvantaged students with the information and guidance they need. Collaboration between college and high school, for example the distribution of college admission information, financial aid opportunities, and college programs could be accomplished under the lead of colleges, where resources are more available. Focus of such collaboration could be placed on high schools in lower SES neighborhoods in order to utilize resources in the most efficient way.

**Guidance for college students**

Once students are enrolled in college, academic counselors could provide lower SES students with special services to help them explore STEM study possibilities. One successful example of promoting lower SES students' performance and persistence in STEM fields is UCLA's Program for Excellence in Education and Research in the Sciences (PEERS). In this program, the institution identifies lower SES students once they are admitted, and selects certain students to participate in a program that provides support for them to persist in STEM fields. Results show that lower SES students who participate in this program are more likely to persist in STEM fields than those who do not participate (Toven-Lindsey, Hasson, & Levis-Fitzgerald, 2013). Similar programs developed by the institutions could help recruit more qualified lower SES students who are not predetermined about their study fields. Such programs could help lower SES students interpret their educational needs and academic preparation before choosing major. For those who are academically well-prepared for STEM fields but are not sure what study to pursue, freshman academic counseling program designed specifically for lower SES students could help students explore various majors and find a good fit. For those who are interested in pursuing STEM studies but lack proper academic preparation, such programs could either provide students with guidance on how to maximize the chance of succeeding in STEM, or point them to another study path that best suits their academic level and education needs.

In order for such programs to be successful, college academic counselors need to understand the educational background, needs, and expectations of lower SES students. Conducting freshman survey could provide relevant information in this aspect and provide counselors with a greater clarity regarding their lower SES students.

**Implications for Future Research**

While this study reveals many interesting findings regarding college students' decisions of STEM majors, it must be noticed that correlations do not reveal causal effects or explain why the observed behaviors happen. The findings of this study suggest further research from various perspectives on the topic of STEM education in college. These include qualitative research on the mechanism of STEM major choice, causal research design, the mechanism of how family SES influences STEM enrollment, and comparison of enrollment in STEM and other majors.

**Qualitative research and causal research design**

This study used quantitative methods to summarize large amount of data and find the underlying trend of STEM enrollment. While it does reveal important findings, many questions remain unanswered. Why are students who attend more expensive colleges less likely to choose STEM majors? Why do higher SES students with high math preparation level prefer STEM majors? To answer these questions, qualitative research is needed.

Quantitative research emphasizes experimental examination or measurement in terms of quantity (Denzin & Lincoln, 2000). It does not examine process or experiences directly, but seek to find out relationship between variables by summarizing large number of cases. Because quantitative research does not address social constraints directly, it loses the richness and depth of study participants' personal experiences and perspectives (Newman & Benz, 1998). As a result, quantitative research does not reveal detailed explanations of social interaction. On the topic of college major choice, quantitative research shows what decisions are made, but does not reveal why such decisions are made.

Qualitative research, on the other hand, addresses personal experiences and interactions. Patton (1990) defines qualitative data as detailed description of behaviors, events, interactions, and quotations from people about their personal experiences, beliefs, perspectives, and attitudes, as well as excerpts from documents and records. Qualitative research emphasizes meaning, process, and description (Denzin & Lincoln, 2000). Due to its descriptive nature, qualitative research is able to record detailed personal experiences, perspectives, and thoughts. It can also directly examine the complexity of social life. As Becker (1996) points out, qualitative researchers are more interested in understanding individual cases and how general laws and statements are reflected in each case. In educational research, these characteristics make qualitative research suitable for answering questions of “how” and “why”. To understand the mechanisms of STEM decision making, qualitative research is necessary. Case study, for example, could reveal how and why a student makes his/her STEM decision. While the findings will not be generalizable, they will provide valuable information for educators and policy makers to improve practice and policy making.

Similar to qualitative research, causal research design is another methodological necessity in the research of STEM decision making and college major choice. Correlational studies only show associations between variables, but do not reveal causal relationship (Guo & Fraser, 2010). To understand which predictors of STEM enrollment are deciding factors, research such as quasi-experimental study or structural equation modeling design are needed (Guo & Fraser, 2010; Kline, 2011). As discussed earlier, although the findings suggest that college selectivity is correlated to STEM enrollment, since the research is correlational rather than causal, it is not clear whether the correlation is due to institutional characteristics, or due to students' interest in certain majors that is formed before they enter college. To fully understand how major decisions are made, research designs that reveal causal relationships are necessary.

**Impact of family SES on STEM education**

The findings of this study suggest that family SES does matter in STEM enrollment in college, but not through the economic perspective as assumed. Further research is needed to explore which component(s) of family SES systematically influence students' STEM decision making and how the mechanism functions. Without better understanding of how family SES influences educational decision making, the efforts to compensate for low SES through targeted academic programs by both high schools and colleges will not be effective. Concepts including social capital and cultural capital may be useful in this line of research (Dumais, 2002; Portes, 1998; Sullivan, 2001). While the findings of this study show that economic concerns are not the deciding factors of STEM enrollment, further research is needed to better understand the role played by financial factors in STEM education.

**Comparison of Enrollment of STEM and Other Majors**

This study examines whether students' family SES is systematically related to STEM enrollment in college. While results suggest that economic concern is not the deciding factor in students' decision making, further investigation is needed to reveal the role played by financial factors in general college major choice. For this purpose, comparison of the enrollment preference in STEM and other majors will be necessary. Such research will reveal the role played by financial factors, whether interest in STEM majors is the main reason for enrollment, and how students compare STEM majors to other majors with comparable financial rewards.

## Conclusion

Promoting STEM enrollment and success is a national mission. This study used a national representative sample of high school students to examine whether family SES is systematically related to students' STEM enrollment in college. Findings suggest that lower SES students are disadvantaged in STEM education, even after controlling for academic preparation. This is reflected in the fact that lower SES students' STEM decisions tend to be less aligned with their academic preparation level than those of higher SES students. This may lead to lower chance of success in STEM for lower SES students, which turns into persistence issue. One widely cited explanation of why disadvantaged students are underrepresented in STEM fields is that due to the demanding study requirements of these majors, students from disadvantaged educational background tend to lack the necessary academic preparation to enroll in STEM fields. The findings of this study show that even when academic preparation level is held equal, lower SES students are still less likely to choose STEM majors in college even when they do have good chance of being successful. Policy makers and educators at both the K-12 and higher education level should be alerted by the fact that STEM fields are losing talent from lower SES background. This is especially relevant given the fact that lower SES students may benefit more from STEM education than higher SES students (Brand & Xie, 2010). Policy makers should also pay attention to the fact that the social and economic stratifications among student groups are being reinforced through the enrollment in STEM majors in college.

While it is discouraging to see that lower SES students are disadvantaged in STEM education, the findings do reveal some encouraging trends regarding underrepresented student groups. Black students, although overall underrepresented in the higher education system (Kim, 2011), are found to be more likely to choose STEM majors in college when other factors are equal. Other minority groups are not less likely to enroll in STEM majors than white students, when other factors are equal. This means that the current gap between racial groups in STEM education is not due to differences in students' preference by racial group. Rather, the question should be how to help underrepresented minority students reach academic status comparable to white students.

Although family SES by itself is not significantly correlated to STEM enrollment, it should be noticed that it does act as a mediating force for factors that are significantly related to STEM enrollment. For factors that lower the STEM enrollment likelihood, family SES reduces the magnitude of the negative correlation. For example, although females are less likely than males to choose STEM majors, the gender gap is smaller among high SES students than among low SES students. For factors that increase the likelihood of STEM enrollment, family SES strengthens the positive correlation. For example, while higher math score is related to higher likelihood of STEM enrollment, the likelihood is even higher among high SES students. In other words, higher family SES makes students advantaged in STEM education.

The findings of this study reveal several important trends in STEM enrollment in college. It should also be noticed that many questions on this topic still warrant further research. For example, what are the deciding factors for higher SES students to prefer STEM majors when academic preparation level is above average? What make STEM majors attractive for them? Do students from different family SES background choose STEM majors for the same reason(s)? Answers to these questions will be the key to promote access to and success in STEM education for the increasingly diverse student body.

APPENDIX
STEM CATEGORIZATION AND MAJOR FIELDS OF STUDY

Table A-1. STEM categorization and major fields of study

| STEM Categorization | Major Field of Study | CIP Major List |
|---|---|---|
| Mathematics | Mathematics and statistics | - Mathematics;<br>- Applied Mathematics;<br>- Statistics;<br>- Mathematics and Statistics, Other; |
| Natural sciences | Agriculture, agriculture operations, and related sciences | - Agriculture, General;<br>- Agricultural Business and Management;<br>- Agricultural Mechanization;<br>- Agricultural Production Operations;<br>- Agricultural and Food Products Processing;<br>- Agricultural and Domestic Animal Services;<br>- Applied Horticulture and Horticultural Business Services;<br>- International Agriculture;<br>- Agricultural Public Services;<br>- Animal Sciences;<br>- Food Science and Technology;<br>- Plant Sciences;<br>- Soil Sciences;<br>- Agriculture, Agriculture Operations, and Related Sciences, Other; |
| | Natural resources and conservation | - Natural Resources Conservation and Research;<br>- Natural Resources Management and Policy;<br>- Fishing and Fisheries Sciences and Management;<br>- Forestry;<br>- Wildlife and Wildlands Science and Management;<br>- Natural Resources and Conservation, Other; |

Table A-1. Continued

| STEM Categorization | Major Field of Study | CIP Major List |
|---|---|---|
| | Biological and biomedical sciences | - Biology, General;<br>- Biochemistry, Biophysics and Molecular Biology;<br>- Botany/Plant Biology;<br>- Cell/Cellular Biology and Anatomical Sciences;<br>- Microbiological Sciences and Immunology;<br>- Zoology/Animal Biology;<br>- Genetics;<br>- Physiology, Pathology and Related Sciences;<br>- Pharmacology and Toxicology;<br>- Biomathematics, Bioinformatics, and Computational Biology;<br>- Biotechnology;<br>- Ecology, Evolution, Systematics, and Population Biology;<br>- Molecular Medicine;<br>- Neurobiology and Neurosciences;<br>- Biological and Biomedical Sciences, Other; |
| | Physical sciences | - Physical Sciences;<br>- Astronomy and Astrophysics;<br>- Atmospheric Sciences and Meteorology;<br>- Chemistry;<br>- Geological and Earth Sciences/Geosciences;<br>- Physics;<br>- Materials Sciences;<br>- Physical Sciences, Other; |
| | Science technologies and technicians | - Science Technologies/Technicians, General;<br>- Biology Technician/Biotechnology Laboratory Technician;<br>- Nuclear and Industrial Radiologic Technologies/Technicians;<br>- Physical Science Technologies/Technicians;<br>- Science Technologies/Technicians, Other; |

Table A-1. Continued

| STEM Categorization | Major Field of Study | CIP Major List |
|---|---|---|
| Engineering and engineering technologies | Engineering | - Engineering, General;<br>- Aerospace, Aeronautical and Astronautical Engineering;<br>- Agricultural Engineering;<br>- Architectural Engineering;<br>- Biomedical/Medical Engineering;<br>- Ceramic Sciences and Engineering;<br>- Chemical Engineering;<br>- Civil Engineering;<br>- Computer Engineering;<br>- Electrical, Electronics and Communications Engineering;<br>- Engineering Mechanics;<br>- Engineering Physics;<br>- Engineering Science;<br>- Environmental/Environmental Health Engineering;<br>- Materials Engineering<br>- Mechanical Engineering;<br>- Metallurgical Engineering;<br>- Mining and Mineral Engineering;<br>- Naval Architecture and Marine Engineering;<br>- Nuclear Engineering;<br>- Ocean Engineering;<br>- Petroleum Engineering;<br>- Systems Engineering;<br>- Textile Sciences and Engineering;<br>- Polymer/Plastics Engineering;<br>- Construction Engineering;<br>- Forest Engineering;<br>- Industrial Engineering;<br>- Manufacturing Engineering;<br>- Operations Research;<br>- Surveying Engineering; |

Table A-1. Continued

| STEM Categorization | Major Field of Study | CIP Major List |
|---|---|---|
| Engineering and engineering technologies | Engineering | - Geological/Geophysical Engineering;<br>- Paper Science and Engineering;<br>- Electromechanical Engineering;<br>- Mechatronics, Robotics, and Automation Engineering;<br>- Biochemical Engineering;<br>- Engineering Chemistry;<br>- Biological/Biosystems Engineering;<br>- Engineering, Other; |
| | Engineering technologies and engineering-related fields | - Engineering Technology, General;<br>- Architectural Engineering Technologies/Technicians;<br>- Civil Engineering Technologies/Technicians;<br>- Electrical Engineering Technologies/Technicians;<br>- Electromechanical Instrumentation and Maintenance Technologies/Technicians;<br>- Environmental Control Technologies/Technicians;<br>- Industrial Production Technologies/Technicians;<br>- Quality Control and Safety Technologies/Technicians;<br>- Mechanical Engineering Related Technologies/Technicians;<br>- Mining and Petroleum Technologies/Technicians;<br>- Construction Engineering Technologies;<br>- Engineering-Related Technologies;<br>- Computer Engineering Technologies/Technicians;<br>- Drafting/Design Engineering Technologies/Technicians;<br>- Nuclear Engineering Technologies/Technicians;<br>- Engineering-Related Fields;<br>- Nanotechnology;<br>- Engineering Technologies/Technicians, Other; |

Table A-1. Continued

| STEM Categorization | Major Field of Study | CIP Major List |
|---|---|---|
| Computer and information sciences | Computer and information sciences and support services | - Computer and Information Sciences, General;<br>- Computer Programming;<br>- Data Processing;<br>- Information Science/Studies;<br>- Computer Systems Analysis;<br>- Data Entry/Microcomputer Applications;<br>- Computer Science;<br>- Computer Software and Media Applications;<br>- Computer Systems Networking and Telecommunications;<br>- Computer/Information Technology Administration and Management;<br>- Computer and Information Sciences and Support Services, Other; |

## LIST OF REFERENCES


Agresti, A., & Finlay, B. (2009). *Statistical methods for the social sciences*. Upper Saddle River, NJ: Pearson Education.

Alexander, K. L., Entwisle, D. R., & Bedinger, S. D. (1994). When expectations work: Race and socioeconomic differences in school performance. *Social Psychology Quarterly, 57*(4), 283-299.

Alexander, F. K., Harnisch, T., Hurley, D., & Moran, R. (2010). Maintenance of effort: An evolving federal-state policy approach to ensuring college affordability. *Journal of Education Finance, 36*(1), 76-87.

Allison, P. D. (1999). *Logistic regression using SAS: Theory and application*. Cary, NC: SAS Institute Inc.

Allison, P. D. (2002). *Missing data*. Thousand Oaks, CA: SAGE.

Anderson, M., & Hearn, J. (1992). Equity issues in higher education outcomes. In W. Becker & D. Lewis (Eds.), *The economics of American higher education* (pp. 301-334). Boston: Kluwer.

Anderson, E. L., & Kim, D. (2006). *Increasing the success of minority students in science and technology*. Washington, D.C.: American Council on Education.

Angle, J., & Wissmann, D. A. (1981). Gender, college major, and earnings. *Sociology of Education, 54*, 25-33.

Arcidiacono, P. (2004). Ability sorting and the returns to college major. *Journal of Econometrics, 121*, 343-375.

Arcidiacono, P., Hotz, V. J., & Kang, S. (2012). Modeling college major choices using elicited measures of expectations and counterfactuals. *Journal of Econometrics, 166*, 3-16.

Ashworth, J., & Evans, J. L. (2001). Modeling student subject choice at secondary and tertiary level: A cross-section study. *Journal of Economic Education, 32*(4), 311-320.

Baum, S., Ma, J., & Payea, K. (2010). *Education pays 2010: The benefits of higher education for individuals and society*. New York: The College Board.

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

Becker, H. S. (1996). Epistemology of Qualitative Research. In R. Jessor, A. Colby, & R. A. Shweder (Eds.), *Ethnography and human development: Context and meaning in social inquiry* (pp. 53-72)*.* Chicago: University of Chicago Press.

Becker, W. E. (1992). Why go to college? The value of an investment in higher education. In W. Becker & D. Lewis (Eds.), *The economics of American higher education* (pp. 91-120). Boston: Kluwer.

Bedard, K., & Herman, D. A. (2008). Who goes to graduate/professional school? The importance of economic fluctuations, undergraduate field, and ability. *Economics of Education Review, 27*, 197-210.

Beecher, M., & Fischer, L. (1999). High school courses and scores as predictors of college success. *Journal of College Admission, 163*, 4-10.

Beede, D., Julian, T., Langdon, D., McKittrick, G., Khan, B., & Doms, M. (2011). *Women in STEM: A gender gap to innovation*. Washington, D.C.: U.S. Department of Commerce.

Beekhoven, S., de Jong, U., & van Hout, H. (2002). Explaining academic progress via combining concepts of integration theory and rational choice theory. *Research in Higher Education, 43*(5), 577-600.

Berger, M. C. (1988). Predicted future earnings and choice of college major. *Industrial and Labor Relations Review, 41*(3), 418-429.

Berger, M. C. (1992). Private returns to specific college majors. In W. Becker & D. Lewis (Eds.), *The economics of American higher education* (pp. 141-171). Boston: Kluwer.

Berkowitz, D., & Hoekstra, M. (2011). Does high school quality matter? Evidence from admissions data. *Economics of Education Review, 30*, 280-288. doi:10.1016/j.econedurev.2010.10.001

Betz, N. E. & Hackett, G. (1983). The relationship of mathematics self-efficacy expectations to the selection of science-based college majors. *Journal of Vocational Behavior, 23*, 329-345.

Black, D. A., Sanders, S., & Taylor, L. (2003). The economic reward for studying economics. *Economic Inquiry, 41*(3), 365-377.

Blau, P. M., & Duncan, O. D. (1967). *The American occupational structure*. New York: John Wiley & Sons.

Borges, N. J., Savickas, M. L., & Jones, B. J. (2004). Holland's theory applied to medical specialty choice. *Journal of Career Assessment, 12*(2), 188-206. doi: 10.1177/1069072703257755

Brackney, K. S. (1993). *A follow-up study investigating the relationships between Holland's personality types and selected career choice variables* (Doctoral dissertation). Retrieved from ProQuest Dissertations & Theses database. (ProQuest document ID: 9319028)

Bradley, R. H., & Corwyn, R. F. (2002). Socioeconomic status and child development. *Annual Review of Psychology, 53*(1), 371-399. doi: 0084-6570/02/0201-0371

Brand, J. E., & Xie, Y. (2010). Who benefits most from college? Evidence for negative selection in heterogeneous economic returns to higher education. *American Sociological Review, 75*(2), 273-302.

Braxton, J. M., & Hargens, L. L. (1996). Variation among academic disciplines: Analytical frameworks and research. In J. C. Smart (Ed.), *Higher education: Handbook of theory and research* (pp. 1-46). New York: Agathon Press.

Bucher, R. (1979). Social structural constraints in career decision making occupational hurdles. In A. M. Mitchell, G. B. Jones, & J. D. Krumboltz (Eds.), *Social learning and career decision making* (pp. 116-133). Cranston, RI: Carroll Press.

Cabrera, A. F., & La Nasa, S. M. (2000). Understanding the college-choice process. *New Directions for Institutional Research, 27*(3), 5-22.

Cameron, J., & Pierce, W. D. (1994). Reinforcement, reward, and intrinsic motivation: A meta-analysis. *Review of Educational Research, 64*(3), 363-423.

Carnevale, A. P., & Desrochers, D. M. (2003). *Standards for what? The economic roots of K-16 reform*. Princeton, NJ: Educational Testing Service.

Carnevale, A. P., & Rose, S. J. (2004). Socioeconomic status, race/ethnicity, and selective college admissions. In R. D. Kahlenberg (Ed.), *America' s untapped resource: Low-income students in higher education* (pp. 101-156). New York: The Century Foundation Press.

Cates, J. T., & Schaefle, S. E. (2011). The relationship between a college preparation program and at-risk students' college readiness. *Journal of Latinos & Education, 10*(4), 320-334.

Cebula, R. J., & Lopes, J. (1982). Determinants of student choice of undergraduate major field. *Educational Research*, *19*(2), 303-312.

Chapman, D. W. (1981). A model of student college choice. *The Journal of Higher Education, 52*(5), 490-505.

Chen, X., & Weko, T. (2009). *Students who study science, technology, engineering, and mathematics (STEM) in postsecondary education*. Washington, D.C.: U.S. Department of Education.

Choi, K. H., Raley, R. K., Muller, C., & Riegle-Crumb, C. (2008). A longitudinal analysis of contextual exposure to peers with college educated parents and students' college enrollment. *Social Science Quarterly, 89*(4), 846-866.

Choi, Y-J., Nam, C-M., &Kwak, M-J. (2004). Multiple imputation technique applied to appropriateness ratings in cataract surgery. *Yonsei Medical Journal, 45*(5), 829-837.

Cohen, J., & Hanno, D. M. (1993). An analysis of underlying constructs affecting the choice of accounting as a major. *Issues in Accounting Education, 8*(2), 219.

Cole, D., & Espinoza, A. (2008). Examining the academic success of Latino students in science technology engineering and mathematics (STEM) majors. *Journal of College Student Development, 49*(4), 285-300.

Cole, J. R., & Cole, S. (1973). *Social stratification in science*. Chicago: University of Chicago Press.

Committee on Equal Opportunities in Science and Engineering. (2004). *Broadening participation in America's science and engineering workforce: The 1994–2003 decennial and 2004 biennial reports to congress*. Arlington, VA: National Science Foundation.

Correll, S. J. (2001). Gender and the career choice process : The role of biased self-assessments. *American Journal of Sociology*, *106*(6), 1691-1730.

Corrigan, M. E. (2003). Beyond access: Persistence challenges and the diversity of low-income students. In J. E. King, E. L. Anderson, & M. E. Corrigan (Eds.), *Changing student attendance patterns: Challenges for policy and practice* (pp. 25-49). San Francisco: Jossey-Bass.

Cowan, C. D., Hauser, R. M., Kominski, R. A., Levin, H. M., Lucas, S. R., Morgan, S. L., ... Chapman, C. (2012). *Improving the measurement of socioeconomic status for the National Assessment of Educational Progress: A theoretical foundation*. Washington, D.C.: National Center for Education Statistics.

Crane, J. (1996). Effects of home environment, SES, and maternal test scores on mathematics achievement. *The Journal of Educational Research, 89*(5), 305-314.

Crisp, G., Nora, A., & Taggart, A. (2009). Student characteristics, pre-college, college, and environmental factors as predictors of majoring in and earning a STEM degree: An analysis of students attending a Hispanic serving institution. *American Educational Research Journal, 46*(4), 924-942.

Crosnoe, R. (2009). Low-income students and the socioeconomic composition of public high schools. *American Sociological Review, 74*(5), 709-730.

Cunningham, W. G., & Sanzo, T. D. (2002). Is high-stakes testing harming lower socioeconomic status schools? *NASSP Bulletin, 86*, 62. doi: 10.1177/019263650208663106

Darling-Hammond, L. (2004). Inequality and the right to learn: Access to qualified teachers in California's public schools. *Teachers College Record, 106*(10), 1936-1966.

Davis, K. D., Winsler, A., & Middleton, M. (2006). Students' perceptions of rewards for academic performance by parents and teachers: Relations with achievement and motivation in college. *Journal of Genetic Psychology, 167*(2), 211-220.

Davies, S. & Guppy, N. (1997). Fields of study, college selectivity, and student inequalities in higher education. *Social Forces, 75*(4), 1417-1438.

Davis-Kean, P. E. (2005). The influence of parent education and family income on child achievement: The indirect role of parental expectations and the home environment. *Journal of Family Psychology, 19*(2), 294-304.

Dawson-Threat, J., & Huba, M. E. (1996, April). *Choice of major and clarity of purpose among college seniors*. Paper presented at the annual meeting of the American Educational Research Association, New York, NY.

Daymont, T. N., & Andrisani, P. J. (1984). Job preferences, college major, and the gender gap in earnings. *The Journal of Human Resources, 19*(3), 408-428.

DeBerard, M. S., Spielmans, G. I., & Julka, D. C. (2004). Predictors Of academic achievement and retention among college freshmen: A longitudinal study. *College Student Journal, 38*(1), 66-80.

Deci, E. L., Koestner, R., & Ryan, R. M. (1999). A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation. *Psychological Bulletin, 125*(6), 627-668.

De Graff, N. K., De Graaf, P. M., & Kraaykamp, G. (2000). Parental cultural capital and educational attainment in the Netherlands: A refinement of the cultural capital perspective. *Sociology of Education, 73*(2), 92-111.

Dennis, J. M., Phinney, J. S., & Chuateco, L. I. (2005). The role of motivation, parental support, and peer support in the academic success of ethnic minority first-generation college students. *Journal of College Student Development, 46*(3), 223-236. doi: 10.1353/csd.2005.0023

Denzin, N. K., & Lincoln, Y. S. (2000). Introduction: The discipline and practice of qualitative research. In N. K. Denzin & Y. S. Lincoln (Eds.), *Handbook of qualitative research* (pp. 1-28). Thousand Oaks, CA: SAGE.

Department of Labor. (2007). *The STEM workforce challenge: The role of the public workforce system in a national solution for a competitive Science, Technology, Engineering, and Mathematics (STEM) workforce*. Washington, D.C.

Deresiewicz, W. (2008). The disadvantages of an elite education: Our best universities have forgotten that the reason they exist is to make minds, not careers. *American Scholar, 77*(3), 20-31.

Desforges, C., & Abouchaar, A. (2003). *The impact of parental involvement, parental support and family education on pupil achievements and adjustment: A literature review*. Nottingham, UK: DfES Publications.

DesJardins, S. L., Dundar, H., & Hendel, D. D. (1999). Modeling the college application decision process in a land-grant university. *Economics of Education Review, 18*, 117-132.

DesJardins, S. L., & Toutkoushian, R. K. (2005). Are students really rational? The development of rational thought and its application to student choice. In J. C. Smart (Ed.), *Higher education: Handbook of theory and research* (pp. 191-240). Dordrecht, Netherlands: Springer.

DeYoung, A. (1989). *Economics and American education: A historical and critical overview of the impact of economic theories on schooling in the United States*. New York: Longman.

Dickson, L. (2010). Race and gender differences in college major choice. In M. C. Long, M. Tienda, & P. Kaniss (Eds.), *Beyond admissions: Re-thinking college opportunities and outcomes* (pp. 108-124). Thousand Oaks, CA: SAGE.

Dresch, S. P. (1979). A quasi-economic view of the career formation process. In A. M. Mitchell, G. B. Jones, & J. D. Krumboltz (Eds.), *Social learning and career decision making* (pp. 134-159). Cranston, RI: Carroll Press.

Dubow, E. F., Boxer, P., & Rowell, L. (2009). Long-term effects of parents' education on children's educational and occupational success. *Merrill-Palmer Quarterly, 55*(3), 224-249.

Dumais, S. A. (2002). Cultural capital, gender, and school success: The role of habitus. *Sociology of Education, 75*(1), 44-68.

Dynan, K. E., & Rouse, C. E. (1997). The underrepresentation of women in economics: A study of undergraduate economics students. *The Journal of Economic Education, 28*(4), 350-368.

Eagan, M. K., & Newman, C. B. (2010, May). *Investing in human capital: Underrepresented racial minorities' intentions to attend graduate school in STEM fields*. Paper presented at the annual meeting of the American Educational Research Association, Denver, CO.

Easterlin, R. A. (1995). Preferences and prices in choice of career: The switch to business, 1972-87. *Journal of Economic Behavior and Organization, 27*, 1-34.

Eccles, J. S. (1994). Understanding women's educational and occupational choices: Applying the Eccles et al. model of achievement-related choices. *Psychology of Women Quarterly, 18*, 585-609.

Eccles, J. S., & Jacobs, J. E. (1986). Social forces shape math attitudes and performance. *Signs, 11*(2), 367-380.

Economics and Statistics Administration. (2011). *STEM: Good jobs now and for the future*. Washington, D.C.: U.S. Department of Commerce.

Edwards, J. R. (2008). Person-environment fit in organizations: An assessment of theoretical progress. In J. P. Walsh & A. P. Brief (Eds.), *The Academy of Management Annals* (pp. 167-230). Hillsdale, NJ: Erlbaum.

Eide, E. (1994). College major choice and changes in the gender wage gap. *Contemporary Economic Policy, 12*(2), 55-64.

Eide, E., & Waehrer, G. (1998). The role of the option value of college attendance in college major choice. *Economics of Education Review, 17*(1), 73-82.

Enders, C. K. (2010). *Applied missing data analysis*. New York: Guilford.

Espinosa, L. L. (2009). *Pipelines and pathways: Women of color in STEM majors and the experiences that shape their persistence*. (Doctoral dissertation). Retrieved from ProQuest Dissertations & Theses database. (ProQuest No. 3394926).

Espinosa, L. L. (2011). Women of color in STEM fields. *Diverse Issues in Higher Education, 28*(16), 9-10.

Ethington, C. A., & Wolfle, L. M. (1988). Women's selection of quantitative undergraduate fields of study: Direct and indirect influences. *American Educational Research Journal, 25*(2), 157-175.

Farmer, H., Rotella, S., Anderson, C., & Wardrop, J. (1998). Gender differences in science, math, and technology careers: Prestige level and Holland interest type. *Journal of Vocational Behavior, 53*, 73-96.

Federman, M. (2007). State graduation requirements, high school course taking, and choosing a technical college major. *The B.E. Journal of Economic Analysis & Policy, 7*(1), 1-32.

Ferry, T. R., Fouad, N. A., & Smith, P. L. (2000). The role of family context in a social cognitive model for career-related choice behavior: A math and science perspective. *Journal of Vocational Behavior, 57*, 348-364.

Fletcher, J., & Tienda, M. (2010). Race and ethnic differences in college achievement: Does high school attended matter? *The ANNALS of the American Academy of Political and Social Science, 627*, 144-166. doi: 10.1177/0002716209348749

Flores, A. (2007). Examining disparities in mathematics education: Achievement gap or opportunity gap? *The High School Journal, 91*(1), 29-42.

Flores, L. Y., Robitschek, C., Celebi, E., Andersen, C., & Hoang, U. (2010). Social cognitive influences on Mexican Americans' career choices across Holland's themes. *Journal of Vocational Behavior, 76*, 198-210.

Foster, M. A., Lambert, R., Abbott-Shim, M., McCarty, F., & Franze, S. (2005). A model of home learning environment and social risk factors in relation to children's emergent literacy and social outcomes. *Early Childhood Research Quarterly, 20*(1), 13-36.

Frehill, L. M. (1997). Education and occupational sex segregation: The decision to major in engineering. *The Sociological Quarterly*, *38*(2), 225-249.

Gabay-Egozi, L., Shavit, Y., & Yaish, M. (2010). Curricular choice: A test of a rational choice model of education. *European Sociological Review, 26*(4), 447-463.

Gamoran, A. (1987). The stratification of high school learning opportunities. *Sociology of Education, 60*, 135-155.

Gandara, P., Rumberger, R., Maxwell-Jolly, J., & Callahan, R. (2003). English learners in California schools: Unequal resources, unequal outcomes. *Education Policy Analysis Archives, 11*(36), 36-90.

Geiger, M. A., & Ogilby, S. M. (2000). The first course in accounting: Students' perceptions and their effect on the decision to major in accounting. *Journal of Accounting Education, 18*, 63-78.

Ghoshl, S., & Pahwa, P. (2006, May). *Design-based versus model-based methods: A comparative study using longitudinal survey data*. Paper presented at the Statistical Society of Canada annual meeting, London, Ontario, Canada.

Gladieux, L. E. (2004). Low-income students and the affordability of higher education. In R. D. Kahlenberg (Ed.), *America' s untapped resource: Low-income students in higher education* (pp. 17-57). New York: The Century Foundation Press.

Gliner, J. A., & Morgan, G. A. (2000). *Research methods in applied settings: An integrated approach to design and analysis*. Mahwah, NJ: Lawrence Erlbaum Associates.

Gneezy, U., Meier, S., & Rey-Biel, P. (2011). When and why incentives (don't) work to modify behavior. *The Journal of Economic Perspective, 25*(4), 191-209.

Gorard, S., See, B. H., & Davies, P. (2012). *The impact of attitudes and aspirations on educational attainment and participation*. York, U.K.: Joseph Rowntree Foundation.

Goyette, K. A., & Mullen, A. L. (2006). Who studies the arts and sciences? Social background and the choice and consequences of undergraduate field of study. *The Journal of Higher Education, 77*(3), 497-538.

Greenberger, E., Lessard, J., Chen, C., & Farruggia, S. P. (2008). Self-entitled college students: Contributions of personality, parenting, and motivational factors. *Journal of Youth and Adolescence, 37*(10), 1193-1204.

Griffith, A. L. (2010). Persistence of women and minorities in STEM field majors: Is it the school that matters? *Economics of Education Review, 29*, 911-922.

Gross, E. (1969). Change in technological and scientific developments and its impact upon the occupational structure. In R. Perrucci & J. E. Gerstl (Eds.), *The engineers and the social system* (pp.17-50). New York: John Wiley & Sons.

Guo, S., & Fraser, M. W. (2010). *Propensity score analysis: Statistical methods and applications*. Thousand Oaks, CA: SAGE.

Hackett, G. (1985). Role of mathematics self-efficacy in the choice of math-related majors of college women and men: A path analysis. *Journal of Counseling Psychology, 32*(1), 47-56.

Hackett, G. (1989). The relationship of role model influences to the career salience and educational and career plans of college women. *Journal of Vocational Behavior*, *35*, 164-180.

Hansen, M. N. (2008). Rational action theory and educational attainment. Changes in the impact of economic resources. *European Sociological Review, 24*(1), 1-17. doi:10.1093/esr/jcm029

Harackiewicz, J. M., Barron, K. E., Tauer, J. M., & Elliot, A. J. (2002). Predicting success in college: A longitudinal study of achievement goals and ability measures as predictors of interest and performance from freshman year through graduation. *Journal of Educational Psychology, 94*(3), 562-575. doi: 10.1037/0022-0663.94.3.562

Harper, S. R. (2010). An anti-deficit achievement framework for research on students of color in STEM. *New Directions for Institutional Research, 148*, 63-74.

Hauser, R. M. (1993). Trends in college entry among Whites, Blacks, and Hispanics, 1972–1988. In C. T. Clotfelter & M. Rothschild (Eds.), *Studies of Supply and Demand in Higher Education* (pp. 61-120), Chicago: University of Chicago Press.

Hazari, Z., Sonnert, G., Sadler, P.M., & Shanahan, M. (2010). Connecting high school physics experiences, outcome expectations, physics identity, and physics career choice: A gender study. *Journal of Research in Science Teaching, 47*(8), 978-1003.

Hearn, J. C. (1984). The relative roles of academic, ascribed, and socioeconomic characteristics in college destinations. *Sociology of Education, 57*(1), 22-30.

Hill, C., Corbett, C., & St. Rose, A. (2010). *Why so few? Women in Science, Technology, Engineering, and Mathematics*. Washington, D.C.: The American Association of University Women.

Holland, J. L. (1966a). A psychological classification scheme for vocations and major fields. *Journal of Counseling Psychology, 13*(3), 278-288.

Holland, J. L. (1966b). *The psychology of vocational choice: A theory of personality types and model environments*. Waltham, MA: Blaisdell.

Holland, J. L. (1997). *Making vocational choices: A theory of vocational personalities and work environments*. Odessa, FL: Psychological Assessment Resources.

Horn, L., & Carroll, C. D. (2006). *Placing college graduation rates in context: How 4-year college graduate rates vary with selectivity and the size of low-income enrollment*. Washington, D.C.: National Center for Education Statistics.

Horn, L. J., Chen, X., & Chapman, C. (2003). *Getting ready to pay for college: What students and their parents know about the cost of college tuition and what they are doing to find out*. Washington, D.C.: National Center for Education Statistics.

Hosmer, D. W., & Lemeshow, S. (1989). *Applied logistic regression*. New York: John Wiley & Sons.

Hossler, D., Schmit, J., & Vesper, N. (1999). *Going to college: How social, economic, and educational factors influence the decisions students make*. Baltimore, MD: John Hopkins University Press.

House, J. D. (2000). Academic background and self-beliefs as predictors of student grade performance in science, engineering and mathematics. *International Journal of Instructional Media, 27*(2), 207-220.

Huang, G., Taddese, N., Walter, E., & Peng, S. S. (2000). *Entry and persistence of women and minorities in college science and engineering education*. Washington, D.C.: U. S. Department of Education.

Huang, Y., & Healy, C. C. (1997). The relations of Holland-typed majors to students' freshman and senior work values. *Research in Higher Education, 38*(4), 455-477.

Hull-Blanks, E., Kurpius, S. E. R., Befort, C., Sollenberger, S., Nicpon, M. F., & Huser, L. (2005). Career goals and retention-related factors among college freshmen. *Journal of Career Development, 32*(1), 16-30.

Hurtado, S., Newman, C. B., Tran, M. C., & Chang, M. J. (2010). Improving the rate of success for underrepresented racial minorities in STEM fields: Insights from a national project. *New Directions for Institutional Research, 148*, 5-15.

Ingels, S. J., Pratt, D. J., Wilson, D., Burns, L. J., Currivan, D., Rogers, J. E., & Hubbard-Bednasz, S. (2007). *Education Longitudinal Study of 2002: Base-year to second follow-up data file documentation (NCES2008-347)*. Washington, D.C.: National Center for Education Statistics.

Kahlenberg, R. D. (2004). Introduction. In R. D. Kahlenberg (Ed.), *America' s untapped resource: Low-income students in higher education* (pp. 1-16). New York: The Century Foundation Press.

Kamens, D. H. (1971). The college "charter" and college size: Effects on occupational choice and college attrition. *Sociology of Education, 44*, 270-296.

Karen, D. (2002). Changes in access to higher education in the United States: 1980-1992. *Sociology of Education, 75*(3), 191-210.

Kelly, S. (2009). The black-white gap in mathematics course taking. *Sociology of Education, 82*, 47-69.

Kim, Y. M. (2011). *Minorities in higher education: Twenty-fourth status report 2010, 2011 supplement*. Washington, D.C.: American Council on Education.

Kincheloe, J. L., & Steinberg, S. R. (2007). *Cutting class: Socioeconomic status and education*. Lanham, MD: Rowman & Littlefield.

Kinzie, J., Palmer, M., Hayek, J., Hossler, D., Jacob, S. A., & Cummings, H. (2004). *Fifty years of college choice: Social, political and institutional influences on the decision-making process*. Indianapolis, IN: Lumina Foundation for Education.

Kirby, E., White, S., & Aruguete, M. (2007). Predictors of white and minority student success at a private women's college. *College Student Journal, 41*(2), 460-465.

Kitsantas, A., Winsler, A., & Huie, F. (2008). Self-regulation and ability predictors of academic success during college: A predictive validity study. *Journal of Advanced Academics, 20*(1), 42-68.

Kline, R. B. (2011). *Principles and practice of structural equation modeling*. New York: Guilford.

Knowles, J. (1997, September). *The influence of socio-economic status on aspirations to enter higher education: School pupils' awareness, understanding and expectations of higher education*. Paper presented at the British Educational Research Association annual conference, York, North Yorkshire, U.K.

Kurlaender, M. (2006). Choosing community college: Factors affecting Latino college choice. *New Directions for Community colleges, 133*, 7-16. doi: 10.1002/cc.223

Langdon, D., McKittrick, G., Beede, D., Khan, B., & Doms, M. (2011). *STEM: Good jobs now and for the future*. Washington, D.C.: U.S. Department of Commerce.

Langelett, G. (2002). Human capital: A summary of the 20th century research. *Journal of Education Finance, 28*, 1-24.

Lee, E. S., & Forthofer, R. N. (2006). *Analyzing complex survey data*. Thousand Oaks, CA: SAGE.

Lee, J. B. (2002). An issue of equity. In D. E. Heller (Ed.), *Condition of access: Higher education for lower income students* (pp. 25-41). Westport, CT: Praeger Publishers.

Lent, R. W., Lopez, F. G., & Bieschke, K. J. (1993). Predicting mathematics-related choice and success behaviors: Test of an expanded social cognitive model. *Journal of Vocational Behavior, 42*, 223-236.

Leong, F. T. L., Austin, J. T., Sekaran, U., & Komarraju, M. (1998). An evaluation of the cross-cultural validity of Holland's theory: Career choices by workers in India. *Journal of Vocational Behavior, 52*(3), 441-455.

Leppel, K., Williams, M. L., & Waldauer, C. (2001). The impact of parental occupation and socioeconomic status on choice of college major. *Journal of Family and Economic Issues*, *22*(4), 373-394.

Leslie, L., & Brinkman, P. (1988). *The economic value of higher education*. New York: Macmillan.

Leslie, L. L., Johnson, G. P., & Carlson, J. (1977). The impact of need-based student aid upon the college attendance decision. *Journal of Education Finance, 2*, 269-285.

Li, Y., Alfeld, C., Kennedy, R. P., & Putallaz, M. (2009). Effects of summer academic programs in middle school on high school test scores, course-taking, and college major. *Journal of Advanced Academics, 20*(3), 404-436.

Little, R. J. A., & Rubin, D. B. (2002).*Statistical analysis with missing data*. Hoboken, NJ: Wiley.

Lopez, G. R. (2001). The value of hard work: Lessons on parent involvement from an (im)migrant household. *Harvard Educational Review, 71*(3), 416-437.

Ma, Y. (2009). Family socioeconomic status, parental involvement, and college major choices - gender, race/ethnic, and nativity patterns. *Sociological Perspectives, 52*(2), 211-234.

Mackenzie, J. (2010). *Public school funding and performance* (Working Paper). Retrieved from http://www.udel.edu/johnmack/research/school_funding.pdf

Malcom, L. E. (2010). Charting the pathways to STEM for Latina/o students: The role of community college. *New Directions for Institutional Research, 148*, 29-40.

Malcom, L. E., & Dowd, A. C. (2012). The impact of undergraduate debt on the graduate school enrollment of STEM baccalaureates. *The Review of Higher Education, 35*(2), 265-305. doi: 10.1353/rhe.2012.0007

Malgwi, C. A., Howe, M. A., & Burnaby, P. A. (2005). Influences on students' choice of college major. *Journal of Education for Business, 80*(5), 275-282.

Maltese, A. V., & Tai, R. H. (2011). Pipeline persistence: Examining the association of educational experiences with earned degrees in STEM among U.S. students. *Science Education, 95*, 877-907. doi: 10.1002/sce.20441

Manski, C. F., & Wise, D. A. (1983). *College choice in America*. Cambridge, MA: Harvard University Press.

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

Marlowe, D., & Crowne, D. P. (1961). Social desirability and response to perceived situational demands. *Journal of Consulting Psychology, 25*(2), 109-115.

Martin, N. K., & Dixon, P. N. (1991). Factors influencing students' college choice. *Journal of College Student Development, 32*, 253-257.

Mason, A., & Monk-Turner, E. (2010). Factors shaping the decision of college students to walk or drive under the influence of alcohol: A test of rational choice theory. *Drugs: Education, Prevention and Policy, 17*(5), 560-572.

Mattila, J. P. (1982). Determinants of male school enrollments: A time series analysis. *Review of Economics and Statistics, 64*, 242-251.

Mayer, D. P., Mullens, J. E., & Moore, M. T. (2001). Monitoring school quality: An indicators report. *Education Statistics Quarterly, 3*(1), 38-44.

Menard, S. W. (2002). *Applied logistic regression analysis*. Thousand Oaks, CA: SAGE.

McDonough, P. M. (1997). *Choosing colleges: How social class and schools structure opportunity*. Albany, NY: State University of New York Press.

McDonough, P. M. (2005). *Counseling and college counseling in America's high schools*. Alexandria, VA: National Association for College Admission Counseling.

McMahon., W. W., & Wagner, A. P. (1981). Expected returns to investment in higher education. *The Journal of Human Resources, 16*(2), 274-285.

Mitchell, C., Kimball, M., Thornton, A., & Young-DeMarco, L. (2008). *The reciprocal relationship between college major and values: Family, careers and society*. Unpublished manuscript, Department of Sociology and Institute for Social Research, University of Michigan, Ann Arbor, MI.

Mixon, N. (2007). Exploring critical theory and critical ethnography in the context of the production and reproduction of social class. In J. L. Kincheloe & S. R. Steinberg (Eds.), *Cutting class: Socioeconomic status and education* (pp. 71-93). Lanham, MD: Rowman & Littlefield.

Mobley, M., & Slaney, R. B. (1996). Holland's theory: Its relevance for lesbian women and gay men. *Journal of Vocational Behavior, 48*, 125-135.

Montmarquette, C., Cannings, K., & Mahseredjian, S. (2002). How do young people choose college majors? *Economics of Education Review, 21*, 543-556.

Mullen, A. L. (2010). *Degrees of inequality: Culture, class, and gender in American higher education*. Baltimore, MD: Johns Hopkins University Press.

Mullis, R. L., Rathge, R., & Mullis, A. K. (2003). Predictors of academic performance during early adolescence: A contextual view. *International Journal of Behavioral Development, 27*(6), 541-548.

Nagelkerke, N. J. D. (1991). A note on a general definition of the coefficient of determination. *Biometrika, 78*, 691–692.

National Center for Public Policy and Higher Education (2008). *Measuring up 2008: The national report card on higher education*. San Jose, CA: The National Center for Public Policy and Higher Education.

National Science Board. (2012). *Science and engineering indicators 2012*. Arlington, VA: National Science Foundation.

National Science Foundation. (2007). *Women, Minorities, and Persons with Disabilities in Science and Engineering: 2007*. Arlington, VA: National Science Foundation.

National Science Foundation. (2010). *Guide to public use data files: Survey of Graduate Students and Postdoctorates in Science and Engineering: Fall 2010*. Arlington, VA.

National Science Foundation. (2011). *STEM education data and trends*. Retrieved from http://www.nsf.gov/nsb/sei/edTool/edTool.html

Need, A., & de Jong, U. (2001). Educational differentials in the Netherlands: Testing rational action theory. *Rationality and Society, 13*(1), 71-98. doi: 10.1177/104346301013001003

Newman, I., & Benz, C. R. (1998). *Qualitative-quantitative research methodology: Exploring the interactive continuum*. Carbondale, Il: Southern Illinois University Press.

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

Norvilitis, J. M., & Reid, H. M. (2012). Predictors of academic and social success and psychological well-being in college students. *Educational Research International, 2012*, 1-6. doi: 10.1155/2012/272030

Ogilvie, J., & Stewart, A. (2010). The integration of rational choice and self-efficacy theories: A situational analysis of student misconduct. *The Australian and New Zealand Journal of Criminology, 43*(1), 130-155.

Ong, A. D., Phinney, J. S., & Dennis, J. (2006). Competence under challenge: Exploring the protective influence of parental support and ethnic identity in Latino college students. *Journal of Adolescence, 29*, 961-979.

Osipow, S. H., & Fitzgerald, L. F. (1996). *Theory of career development*. Needham Heights, MA: Allyn & Bacon.

Parker, J. D. A., Creque, R. E., Barnhart, D. L., Harris, J. I., Majeski, S. A., Wood, L. M., ...Hogan, M. J. (2004). Academic achievement in high school: Does emotional intelligence matter? *Personality and Individual Differences, 37*, 1321-1330.

Pascarella, E., & Terenzini, P. (1991). *How college affects students*. San Francisco: Jossey-Bass.

Patton, M. Q. (1990). *Qualitative evaluation and research methods*. Newbury Park, CA: SAGE.

Paulsen, M. B., & St. John, E. P. (1997). The financial nexus between college choice and persistence. *New Directions for Institutional Research, 95*, 65-82.

Paulsen, M. B., & St. John, E. P. (2002). Social class and college costs: Examining the financial nexus between college choice and persistence. *The Journal of Higher Education, 73*(2), 189-236.

Peard, R. F. (2004). School mathematical achievement as a predictor of success in a first year university mathematics foundations unit. In I. Putt, R. Faragher, & M. McLean (Eds.), *Proceedings MERGA 2004* (pp. 422-429). Townsville, Qld, Australia.

Pearson, C. (1997). Parental influence on a student's selection of a college major. *College Student Journal, 31*(3), 301-313.

Pender, M., Marcotte, D. E., Domingo, M. R. S., & Maton, K. I. (2010). The STEM pipeline: The role of summer research experience in minority students' Ph.D. aspirations. *Education Policy Analysis Archives, 18*(30), 1-39.

Perna, L. W. (2005). The benefits of higher education: Sex, racial/ethnic, and socioeconomic group differences. *The Review of Higher Education, 29*(1), 23-52.

Perna, L. W. (2006). Student college access and choice: A proposed conceptual model. In J. C. Smart (Ed.), *Higher education: Handbook of theory and research* (pp. 99-157). Dordrecht, Netherlands: Springer.

Perna, L. W., Gasman, M., Gary, S., Lundy-Wagner, V., & Drezner, N. D. (2010). Identifying strategies for increasing degree attainment in STEM: Lessons from minority-serving institutions. *New Directions for Institutional Research, 148*, 41-51.

Perna, L. W., & Titus, M. A. (2004). Understanding differences in the choice of college attended: The role of state public policies. *The Review of Higher Education, 27*(4), 501-525. doi: 10.1353/rhe.2004.0020

Pike, G. R. (2007, June). *Using weighting adjustments to compensate for survey nonresponse*. Paper presented at the annual meeting of the Association for Institutional Research, Kansas City, MO.

Pike, G. R., & Saupe, J. L. (2002). Does high school matter? An analysis of three methods of predicting first-year grades. *Research in Higher Education, 43*(2), 187-207. doi: 0361-0365/02/0400-0187/0

Pitre, P. E. (2006). College choice: A study of African American and white student aspirations and perceptions related to college attendance. *College Student Journal, 40*(3), 562-574.

Porter, S. R., & Umbach, P. D. (2006). College major choice: An analysis of person-environment fit. *Research in Higher Education, 47*(4), 429-449.

Portes, A. (1998). Social capital: Its origins and applications in modern sociology. *Annual Review of Sociology, 24*, 1-24.

President's Council of Advisors on Science and Technology. (2012). *Engage to excel: Producing one million additional college graduates with degrees in science, technology, engineering, and mathematics*. Washington, D.C.

Price, J. (2010). The effect of instructor race and gender on student persistence in STEM fields. *Economics of Education Review, 29*(6), 901-910.

Pryor, J. H., Hurtado, S., DeAngelo, L., Blake, L. P., & Tran, S. (2009). *The American freshman: National norms fall 2009*. Los Angeles: Higher Education Research Institute, UCLA.

Qian, Y., & Zafar, B. (2010, January). *Do female faculty influence female students' choice of college major, and why*? Paper presented at the Allied Social Sciences Association annual meeting, Atlanta, GA.

Raghunathan, T. E., Lepkowski, J. M., Hoewyk, J. V., & Solenberger, P. (2001). A multivariate technique for multiply imputing missing values using a sequence of regression models. *Survey Methodology, 27*(1), 85-95.

Rampell, C. (2011). *The college majors that do best in the job market*. Retrieved from http://economix.blogs.nytimes.com/2011/05/19/the-college-majors-that-do-best-in-the-job-market/

Rask, K. (2010). Attrition in STEM fields at a liberal arts college: The importance of grades and pre-collegiate preferences. *Economics of Education Review, 29*, 892-900.

Rask, K. N., & Bailey, E. M. (2002). Are faculty role models? Evidence from major choice in an undergraduate institution. *The Journal of Economic Education, 33*(2), 99-124.

Rask, K., & Tiefenthaler, J. (2008). The role of grade sensitivity in explaining the gender imbalance in undergraduate economics. *Economics of Education Review, 27*, 676-687.

Rice, J. K. (2003). *Teacher quality: Understanding the effectiveness of teacher attributes*. Washington, D.C.: Economic Policy Institute.

Riegle-Crumb, C., & King, B. (2010). Questioning a white male advantage in STEM: Examining disparities in college major by gender and race/ethnicity. *Educational Researcher, 39*(9), 656-664.

Rothstein, H. R., Sutton, A. J., & Borenstein, M. (2005). *Publication bias in meta-analysis: Prevention, assessment and adjustments*. Hoboken, NJ: Wiley.

Rowan-Kenyon, H. T. (2007). Predictors of delayed college enrollment and the impact of socioeconomic status. *The Journal of Higher Education, 78*(2), 188-214.

Rowan-Kenyon, H. T., Bell, A. D., & Perna, L. W. (2008). Contextual influences on parental involvement in college going: Variations by socioeconomic class. *The Journal of Higher Education, 79*(5), 564-586.

Rubin, D. B. (1996). Multiple imputation after 18+ years. *Journal of the American Statistical Association, 91*, 473-489.

Rumberger, R. W. (1984). The changing economic benefits of college graduates. *Economics of Education Review, 3*(1), 3-11.

Rumberger, R. W., & Palardy, G. J. (2005). Does segregation still matter? The impact of student composition on academic achievement in high school. *Teachers College Record, 107*(9), 1999-2045.
Rumberger, R. W., & Thomas, S. L. (1993). The economic returns to college major, quality and performance: A multilevel analysis of recent graduates. *Economics of Education Review, 12*(1), 1-19.

Sanderson, M. (1993). Vocational and liberal education: A historian's view. *European Journal of Education, 28*(2), 189-196.

Schreiber, J. B. (2002). Institutional and student factors and their influence on advanced mathematics achievement. *The Journal of Educational Research, 95*(5), 274-286.

Schultz, T. W. (1961). Investment in human capital. *The American Economic Review, 51*(1), 1-17.

Scott, J. (2000). Rational choice theory. In G. Browning, A. Halcli, & F. Webster (Eds.), *Understanding contemporary society: Theories of the present* (pp. 126-138). Thousand Oaks, CA: SAGE.

Seymour, E., & Hewitt, N. M. (1997). *Talking about leaving: Why undergraduates leave the sciences*. Boulder, CO: Westview.

Shieh, Y.-Y. (2003, November). *Imputation methods on general linear mixed models of longitudinal studies*. Paper presented at the Federal Committee on Statistical Methodology Research Conference, Arlington, VA.

Shin, J. C., & Milton, S. (2008). Student response to tuition increase by academic majors: Empirical grounds for a cost-related tuition policy. *Higher Education, 55*, 719-734.

Sianou-Kyrgiou, E. (2010). Stratification in higher education, choice and social inequalities in Greece. *Higher Education Quarterly, 64*(1), 22-40. doi: 10.1111/j.1468-2273.2009.00427.x

Simpson, J. C. (2001). Segregated by subject: Racial differences in the factors influencing academic major between European Americans, Asian Americans, and African, Hispanic, and native Americans. *The Journal of Higher Education, 72*(1), 63-100.

Singh, K., Bickley, P. G., Keith, T. Z., Keith, P. B., Trivette, P., & Anderson, E. (1995). The effects of four components of parental involvement on eighth grade student achievement: Structural analysis of NELS-88 data. *School Psychology Review, 24*(2), 299-317.

Smith, J. A. (2010). *Differences in personality factors and college major choice* (Master's Thesis). Retrieved from ProQuest Dissertations & Theses database. (ProQuest document ID: 1508158).

Smith, F. M., & Hausafus, C. O. (1998). Relationship of family support and ethnic minority students' achievement in science and mathematics. *Science Education, 82*(1), 111-125.

Smyth, F. L., & McArdle, J. J. (2004). Ethnic and gender differences in science graduation at selective colleges with implications for admission policy and college choice. *Research in Higher Education, 45*(4), 353-381.

Solmon, L. C. (1981). New findings on the links between college education and work. *Higher Education, 10*(6), 615-648.

Song, C., & Glick, J. E. (2004). College attendance and choice of college majors among Asian-American students. *Social Science Quarterly, 85*(5), 1401-1421.

Spera, C. (2005). A review of the relationship among parenting practices, parenting styles, and adolescent school achievement. *Educational Psychology Review, 17*(2), 125-146. doi: 10.1007/s10648-005-3950-1

St. John, E. P. (1994a). *Prices, productivity, and investment: Assessing financial strategies in higher education*. Washington, D.C.: The George Washington University.

St. John, E. P. (1994b). The influence of debt on choice of major. *Journal of Student Financial Aid, 24*(1), 5-12.

St. John, E. P., Asker, E. H., & Hu, S. (2001). The role of finances in student choice: A review of theory and research. In M. B. Paulsen & J. C. Smart (Eds.), *The finance of higher education: Theory, research, policy, and practice* (pp. 419-438). New York: Agathon.

St. John, E. P., Hu, S., Simmons, A., Carter, D. F., & Weber, J. (2004). What difference does a major make? The influence of college major field on persistence by African American and white students. *Research in Higher Education, 45*(3), 209-232.

St. John, E. P., Paulsen, M. B., & Carter, D. F. (2005). Diversity, college costs, and postsecondary opportunity: An examination of the financial nexus between college choice and persistence for African Americans and whites. *The Journal of Higher Education, 76*(5), 545-569.

St. John, E. P., Paulsen, M. B., & Starkey, J. B. (1996). The nexus between college choice and persistence. *Research in Higher Education, 37*(2), 175-220.

Staniec, J. F. O. (2004). The effects of race, sex, and expected returns on the choice of college major. *Eastern Economic Journal, 30*(4), 549-562.

Sullivan, A. (2001). Cultural capital and educational attainment. *Sociology, 35*(4), 893-912. doi: 10.1177/0038038501035004006

Sullivan, A. (2006). Students as rational decision-makers: The question of beliefs and attitudes. *London Review of Education, 4*(3), 271-290.

Swail, W. S. (2000). Preparing America's disadvantaged for college: Programs that increase college opportunity. *New Directions for Institutional Research, 27*(3), 85-101.

Swail, W. S., Cabrera, A. F., Lee, C., & Williams, A. (2005). *Latino students & the educational pipeline. Part III: Pathways to the bachelor's degree for Latino students*. Washington, D.C.: Educational Policy Institute.

Tannen, M. B. (1978). The investment motive for attending college. *Industrial and Labor Relations Review, 31*(4), 489-497.

Tate, W. F. (1997). Race-ethnicity, SES, gender, and language proficiency trends in mathematics achievement: An update. *Journal for Research in Mathematics Education, 28*(6), 652-679.

Teachman, J. D. (1987). Family background, educational resources, and educational attainment. *American Sociological Review, 52*(4), 548-557.

Terenzini, P. T., Cabrera, A. F., & Bernal, E. M. (2001). *Swimming against the tide: The poor in American higher education*. New York: College Entrance Examination Board.

Thomas, G. E. (1985). College major and career inequality: Implications for black students. *The Journal of Negro Education*, *54*(4), 537-547.

Thompson, J. S. (2003). The effect of single-sex secondary schooling on women's choice of college major. *Sociological Perspectives, 46*(2), 257-278.

Tornatzky, L. G., Cutler, R., & Lee, J. (2002). *College knowledge: What Latino parents need to know and why they don't know it*. Claremont, CA: Tomas Rivera Policy Institute.

Toven-Lindsey, B., Hasson, T., & Levis-Fitzgerald, M. (2013, May). *Academic support for underrepresented STEM students: Satisfaction and impact*. Paper presented at the Association for Institutional Research annual forum, Long Beach, CA.

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.

Trusty, J., & Ng, K. (2000). Longitudinal effects of achievement perceptions on choice of postsecondary major. *Journal of Vocational Behavior, 57*, 123–135. doi:10.1006/jvbe.1999.1735.

Trusty, J., Ng, K., & Ray, D. (2000). Choice of Holland's social type college majors for U.S. racial/ethnic groups. *Journal of Career Development, 27*(1), 49-64.

Trusty, J., Robinson, C. R., Plata, M., & Ng, K.-M. (2000). Effects of gender, socioeconomic status, and early academic performance on postsecondary educational choice. *Journal of Counseling & Development, 78*, 463-472.

Turner, S. E., & Bowen, W. G. (1999). Choice of major: The changing (unchanging) gender gap. *Industrial and Labor Relations Review*, *52*(2), 289-313.

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

United States Department of Education. (2005). *10 facts about K-12 education funding*. Washington, D.C.

United States Government Accountability Office. (2005). *Federal Science, Technology, Engineering, and Mathematics Programs and Related Trends*. Washington, D.C. Retrieved from http://www.gao.gov/new.items/d06114.pdf

University of Michigan. (2011). *IVEware: Imputation and variance estimation version 0.2 users guide*. Ann Arbor, MI: University of Michigan.

Unruh, W. R. (1979). Career decision making: Theory construction and evaluation. In A. M. Mitchell, G. B. Jones, & J. D. Krumboltz (Eds.), *Social learning and career decision making* (pp. 5-18). Cranston, RI: Carroll Press.

Van de Werfhorst, H. G. (2002). A detailed examination of the role of education in intergenerational social-class mobility. *Social Science Information, 41*, 407-438. doi: 10.1177/0539018402041003004

Walpole, M. (2003). Socioeconomic status and college: How SES affects college experiences and outcomes. *The Review of Higher Education, 27*(1), 45-73.

Walpole, M. (2008). Emerging from the pipeline: African American students, socioeconomic status, and college experiences and outcomes. *Research in Higher Education, 49*, 3, 237-255.

Wang, S-T., Yu, M-L., & Lin, L-Y.(1997). Consequences of analysing complex survey data using inappropriate analysis and software computing packages. *Public Health, 111*, 259-262.

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

Watson, C. N. (2012). *Using factors of socioeconomic status, family support, and academic preparation to explain the black-white gap in mathematics achievement and participation* (Doctoral dissertation). Retrieved from ProQuest Dissertations & Theses database. (ProQuest document ID: 3512366).

Wayman, J. C. (2003, April). *Multiple imputation for missing data: What is it and how can I use it?* Paper presented at the annual meeting of the American Educational Research Association, Chicago, IL.

Wayne, A. J., & Youngs, P. (2003). Teacher characteristics and student achievement gains: A review. *Review of Educational Research, 73*(1), 89-122.

White, K. R. (1982). The relation between socioeconomic status and academic achievement. *Psychological Bulletin, 91*(3), 461-481.

Willis, R. J., & Rosen, S. (1979). Education and self-selection. *Journal of Political Economy, 87*(5), S7-S36.

Worthington, A. C., & Higgs, H. (2003). Factors explaining the choice of a finance major: The role of students' characteristics, personality and perceptions of the profession. *Accounting Education*, *12*(3), 261-281. doi:10.1080/0963928032000088831.

Wyner, J. S., Bridgeland, J. M., & DiIulio, J. J. (2007). *Achievementrap: How America is failing millions of high-achieving students from lower-income families*. Washington, D.C.: Civic Enterprises.

Xie, Y., & Goyette, K. (2003). Social mobility and the educational choices of Asian Americans. *Social Science Research, 32*, 467-498.

Young, H. (2005). Secondary education systemic issues: Addressing possible contributors to a leak in the science education pipeline and potential solutions. *Journal of Science Education and Technology, 14*(2), 205-216. doi: 10.1007/s10956-005-4422-6

Zimmerman, B. J., Bandura, A., & Martinez-Pons, M. (1992). Self-motivation for academic attainment: The role of self-efficacy beliefs and personal goal setting. *American Educational Research Journal, 29*(3), 663-676.