Should We Still be Talking About Leaving?

A Comparative Examination of Social Inequality in Undergraduate Patterns of Switching Majors

WCER Working Paper No. 2014-5

November 2014

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Ferrare. J. J., & Lee, Y. G. (2014). *Should We Still be Talking About Leaving? A Comparative Examination of Social Inequality in Undergraduates' Major Switching Patterns* (WCER Working Paper No. 2014-5). Retrieved from University of Wisconsin–Madison, Wisconsin Center for Education Research website: http://www.wcer.wisc.edu/publications/workingPapers/papers.php

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Joseph J. Ferrare and You-Geon Lee

Switching majors from one field of study to another is often thought to be a natural and productive part of the undergraduate experience—a process by which students find the best fit for their needs, interests, and aspirations. Yet, in fields with strong social closure, such as the science, technology, engineering, and mathematics (STEM) disciplines, students' decisions to switch their major from one field to another do not always fit the innocence of this functionalist explanation. Instead, many students switch because of conflicts they experience in the social and cultural conditions encountered in these fields (Seymour & Hewitt, 1997). As a result, questions concerning recruitment and retention as well as achievement and attainment in STEM disciplines have become key problematics in the social sciences. There are many reasons for this heightened emphasis on STEM fields. Most notable to sociologists, for example, is that STEM fields represent a persistent source of horizontal differentiation even as the higher education system has expanded dramatically towards inclusivity over the past few decades (Bradley, 2000; Goldrick-Rab & Cook, 2011). Further, despite extensive efforts to bring gender and racial diversity to STEM fields, scholars have identified numerous challenges that continue to stand in the way of meaningful change toward this end (Blickenstaff, 2005; Ong et al., 2012).

Heightened interest in STEM issues among researchers is also linked to the broader policy relevance these issues are perceived to have in economic and political fields of action. Policymakers draw upon a variety of discourses to advance the importance of STEM education. By far the most prevalent is what we will call the "economic vitality discourse" (e.g., National Science Board, 2010), which states that STEM education is crucial to economic stability because current estimates indicate that occupations requiring at least some postsecondary STEM education are the fastest growing sectors of the economy (Carnevale, Smith, & Melton, 2011). This neoliberal discourse also connects to broader conservative discourses about American exceptionalism and national security interests (Apple, 2006). While these discourses speak to current and future projections, they also have long been a policy tool used by politicians in broader global struggles. For instance, in his 1958 State of the Union Address and partly as a response to the crisis caused by the Sputnik launch, Eisenhower called for increased attention to STEM education. Nearly every president since has used STEM education as a discursive tool to advance economic and state interests.

While policymakers tend to emphasize the technocratic importance of STEM education, others approach the issue from the perspective of social equity. According to the social equity discourse, if STEM fields are linked to vital positions within our economic and political structures then it is imperative to address the persistent inequities in these fields so that doors of opportunity open in the future (Ong et al., 2012). In particular, given the historical exclusion of women and students of color from these majors and occupations, any attempt to bolster the recruitment and retention of students into STEM fields should include strong efforts to address the cultural and economic incongruence that historically marginalized students experience in these fields. Even if the perceived link between STEM majors and economic vitality is overstated (see Teitelbaum, 2014), systematic racial, gender, and/or class-based patterns of entry to and departure from STEM fields—especially if these patterns are unique to STEM—potentially violate social equity goals and even moderate conceptions of justice (e.g., Nussbaum, 2011).

While there have been extensive efforts to recruit and retain undergraduates majoring in STEM fields, there is surprisingly little understanding of recent patterns of switching to and from STEM majors and whether these patterns are unique or part of a process that permeates other majors in higher education. Using the most recent cohort (2004/2009) of undergraduate students from the Beginning Postsecondary Student Longitudinal Study (BPS:04/09), we examine the patterns of switching to and from STEM and non-STEM majors and test a series of theoretically-specified logistic regression models of switching. The goal is to better understand the factors associated with changes in these patterns. In particular, our analysis seeks to answer the following questions: (1) What are the patterns of switching to and from majors in STEM, education, humanities, social sciences, health sciences, and business? (2) Are there gender, racial, and/or economic variations to these patterns after accounting for associations related to institutional contexts, high school preparation, and undergraduate coursetaking and performance? (3) If there are systematic differences in the switching patterns across gender, race, and/or class, are these differences specific to certain majors or germane to the entire higher education system?

To address these questions we specify our models of major-switching using four prominent theories of undergraduate persistence in the literature: (1) Tinto's (Durkheimian) model of social and academic integration, (2) social and cultural reproduction theory, (3) rational choice theory, and (4) institutional effects. While each theory anticipates different relationships as to why a student may or may not switch from one major to another, when taken together they offer insights into the academic, cultural, economic, and institutional contexts of students' switching and persistence decisions. In addition, these models provide a basis from which to consider whether or not switching from STEM to non-STEM majors violates the normative goal of social equity in high-status fields constituted by strong social closure. If this goal is violated, our approach allows us to ask whether any of our models suggest certain policy objectives for enhancing equity in higher education and, ultimately, access to positions of power in other institutions in society.

Literature Review

Locating the sources of underrepresentation among historically marginalized populations in STEM fields has proven to be a complex task given the numerous intersecting contexts that can potentially shape these patterns (Blickenstaff, 2005; Eccles, 2007). This appears to be especially true for women's participation in STEM. Indeed, recent trends suggest that outside of the life sciences the gender gap in STEM fields has changed very little over the past 30 years—and has even widened in engineering (Mann & DiPrete, 2013). Efforts to understand these trends have often encountered contradictory and inconsistent findings in the literature (Ceci, Williams, & Barnett, 2009). Nevertheless, the collection of more nuanced datasets and a critical mass of researchers have led to important insights. For example, recent work has consistently rejected the hypotheses that variation in high school preparation explains the persistent gender differences in entry into STEM majors (Riegle-Crumb et al., 2012), or that these differences are largely a function of background or life goals (Mann & DiPrete, 2013).

With these mythical explanations ruled out, researchers have focused significant attention on understanding the socialization processes (Archer et al., 2012), local school contexts (Ayalon, 2003; Frank, Muller, & Schiller, 2008; Legewie & DiPrete, 2014), and the pre-collegiate development of occupational goals (Morgan, Gelbgiser, & Weeden, 2013) that shape the pathways leading into undergraduate STEM majors. These pre-collegiate areas of emphasis have produced critical understandings of how students develop dispositions favorable to science and math by focusing on familial contexts (e.g., cultural capital) and the extent to which local social structures in primary and secondary schools influence these dispositions across multiple stages of education development (see also Adamuti-Trache & Andres, 2008). Legewie and DiPrete (2014), for example, found that school-level gender segregation in STEM courses has a significant impact on female high school students' plans to major in a STEM field. Thus, while familial and other forms of differential socialization play a sizeable role in the STEM gender gap, forms of social organization in education institutions also have an autonomous impact on these trends.

Although pre-collegiate contexts are important to understanding the persistent social and cultural differentiations in STEM majors and occupations, social scientists have also focused extensively on the local contexts of institutions of higher education (IHEs). Similar to the findings that girls' STEM orientations can be shaped by local patterns of high school coursetaking, researchers have begun to investigate the social structures that emerge from the patterns of coursetaking at the undergraduate level. For instance, Mann and DiPrete (2013) found that female STEM majors have more diverse coursetaking trajectories and take more courses in the humanities and social sciences than male STEM majors. The authors hypothesize that competition between majors and the curricular structure of IHEs interact with occupational goals and preferences for a liberal arts education in ways that lead to a stagnant (and in some cases widening) gender gap in STEM fields. Adding indirect support to this conjecture are additional studies that find that students—especially female students—are lured out of STEM majors by better grades in non-STEM fields (Ost, 2010).

The body of research that examines factors pushing and pulling students away from STEM majors has been strongly influenced by Seymour's and Hewitt's (1997) *Talking About Leaving: Why Undergraduates Leave the Sciences*, which, in addition to pre-collegiate factors, identified a range of pedagogical and curricular qualities of STEM majors that lead students to switch out of these disciplines to other fields of study. Focusing on the local contexts of IHEs has also been complemented by an emphasis on the conflicting identities and cultural incongruence that underrepresented groups negotiate in STEM majors (Cole & Espinoza, 2008; Johnson, Brown, Carlone, & Cuevas, 2011), as well as the practices that IHEs can adopt to better support these students (Hyde & Gess-Newsome, 1999). More recent work has generally supported the original findings in *Talking About Leaving*, especially related to the ways that faculty and peers can significantly impact the likelihood that women and students of color already majoring in a STEM discipline will persist toward graduation (Gayles & Ampaw, 2014; Price, 2010).

A report issued by the National Center for Education Statistics (NCES) (Chen, 2013) analyzed the 2004/2009 cohort from the BPS and found that rates of switching from STEM to non-STEM majors in bachelor's programs ranges from 20% in engineering to 30% in mathematics. Overall, 28% of beginning STEM majors switched to non-STEM fields, and an additional 20% left postsecondary education altogether without a degree or certificate by the time of the 2009 follow-up survey. The researchers found that these rates were not unique. In fact, students entering the fields of education (42%) and humanities (33%) had higher rates of switching to other major field categories, with rates in business (27%) and social science (28%) being about the same as those in STEM fields.

While these rates of switching are informative on their own, the NCES researchers also sought to examine whether these patterns are associated with key variables of interest. Importantly, they found that female students are more likely to switch out of STEM majors in bivariate analysis, but that these findings did not hold once a variety of coursetaking and performance variables were included in the model. However, the NCES report included only a limited range of covariates in the analysis and did not present a discernable theoretical rationale for this specification, other than to note that the BPS has a limited number of variables. Most notably, the report does not include available covariates related to students' financial contexts (e.g., loans, need to work) or social interactions with faculty and students; nor does it model the possibility of disciplinary heterogeneity. Even with the limited covariates, moreover, the report does not model switching patterns in non-STEM majors. As we will demonstrate below, these limitations have important consequences for our understanding of students' patterns of switching majors.

Theorizing Switching Majors

Sociologists and social scientists more generally have used a variety of theories to better understand patterns of persistence and departure in higher education. These theories traverse an expansive terrain within the literature, including sociology, psychology, social psychology, anthropology, economics, and education. It is not our intent to explore these theories in detail here (see Melguizo, 2011 for a review). Rather, in this section we introduce the theoretical perspectives that guide our analysis of major switching. Much of our discussion is situated in the sociological literature, but in some cases we draw upon research germane to the more general literature on higher education and persistence.

Tinto's theory of integration. The most popular theory of higher education persistence and departure in the literature is Tinto's (1975) Durkheimian framework of student departure. Similar to how Durkheim viewed suicide, Tinto's theory conceptualizes student departure (e.g., dropping out) from various contexts of higher education as the result of failed integration into the social structure of local academic and social environments. For Tinto (1997), the foundation of social and academic integration is established in the classroom. Classroom practices and interactions such as small group discussions and study groups are seen as influencing students' social and academic integration, which, in turn, influences their likelihood of persisting within that environment. Research suggests that college students' first-year curricular experiences, in particular, may reinforce and alter their expectations and preferences and, consequently, influence their decisions about their subsequent coursetaking and major field of study (Attewell, Heil, & Reisel, nd; Chen, 2013; Crisp, Nora, & Taggart, 2009; Huang, Taddese, & Walter, 2000; Stinebrickner & Stinebrickner, 2011).

In our analysis we attempt to specify a model of social and academic integration to examine whether or not these processes are associated with a change in the probability of switching majors—net a variety of covariates. In particular, Tinto's theory would generate hypotheses that increased academic integration (as measured by coursetaking and GPA in major field of study) and social integration (interactions with faculty, membership in clubs and study groups) should reduce the likelihood of "disciplinary anomie" and switching to a major in a different discipline. Recent evidence suggests that female students are particularly responsive to social integration in STEM fields via faculty interactions, but interactions with peers through study groups may actually work in the opposite direction (Gayles & Ampaw, 2014). While some have argued that the empirical evidence supporting Tinto's theory has been relatively weak in relation to student departure from postsecondary education (Braxton, Shaw Sullivan, & Johnson Jr., 1997), our goal is to test this assertion directly in the context of switching undergraduate majors.

Social and cultural reproduction. While Tinto's Durkheimian theory of integration may be the most widely used in the higher education literature, theories of social and cultural reproduction are likely to be the most familiar and popular among sociologists. Influenced to a great extent by Bourdieu (1996; see also Bourdieu & Passeron, 1977) and Bernstein (1977), among others, reproduction theorists argue that exogenous social and cultural relations become retranslated as educational practices within educational institutions and systems. Thus, these theorists point to the importance of understanding familial class background (especially education), gender and race relations, and other social dynamics that reemerge as patterns of educational practices that are similar in form, if not substance, to exogenous social relations.

Sociologists of education have made ample use of reproduction theories to examine practices and patterns in higher education in general and STEM fields in particular. For instance, Tierney (1999) draws on cultural capital theory to examine minority student college-going and retention. In the context of STEM disciplines, Bradley (2000) and Adamuti-Trache and Andres (2008) utilize reproduction theory to explain the persistent gender differentiation in higher education majors despite decades of expansion. Within the reproduction framework, it is to be expected, given gender-differentiated relations in other fields of social life, that women will continue to choose majors outside of STEM fields at relatively steady rates despite dramatic increases in college going.

In the present analysis we use a range of variables from the BPS:04/09 dataset to test whether or not gender, race, and parental social class (i.e., education and income) are associated with meaningful changes in the likelihood of switching from one major group to another. In addition, we include measures of academic preparedness upon entering postsecondary education as proxies for the interactions between families' and students' strategic use of skills and competencies and the evaluative criteria used by educational institutions (see Lareau & Weininger, 2003). That is, rather than attempting to partition abilities and skills from cultural capital, here it is assumed that these practices and dispositions are bound by the same broader set of social and cultural relations. One might argue that college GPA is a similar proxy for these cultural relations. However, to directly test Tinto's theory, we model the latter variable as a form of academic integration. In addition, we assume that prior forms of academic integration—once successful—are converted into cultural capital and used in future social transactions. In future theoretical development it may make more sense to consider academic and social integration as a set of practices through which social and cultural reproduction take place. Indeed, we lay the groundwork for this proposition in our discussion below.

Rational choice theory. Rational choice theory is grounded in the notion that humans make decisions through cost/benefit analysis in an attempt to maximize personal advantages. Economists such as Friedman (1954) and Becker (1967) are primarily responsible for the proliferation of rational choice theories used to examine education. More recently, researchers such as Manski and Wise (1983) and Cameron and Heckman (1998) have extended these approaches to focus on specific questions related to college student behavior, including persistence. Sociologists (e.g., Breen and Goldthorpe [1997] and Morgan [2005]) have also utilized rational choice theory to examine education persistence and attainment. The primary difference between the way sociologists and economists use rational choice theory in this context is that the former tend to focus on the implications of these choices on stratification processes whereas the latter tend to focus on individual decision making (Melguizo, 2011).

In the context of rational choice theory one would expect that students' switching decisions would result from efforts to maximize the utility of their chosen education trajectories. In this sense, students would consider factors such as financial aid (e.g., loans or parental support), cost of attendance, the need to work while enrolled, and the effort required for attainment, and then weigh these factors against the potential payoff in the occupational structure. Thus, a rational choice theorist may reasonably expect that changes in these factors will be associated with changes in the probability of switching from a STEM major to a non-STEM discipline. We put these expectations to the test in our logistic regression models below.

Institutional effects. Researchers interested in college student persistence in general and STEM in particular have increasingly looked to the institutional contexts in which students make decisions—rational or otherwise—related to their choice of major. The assumption in the institutional effects literature is that even though exogenous factors such as gender, race, and class relations may shape the educational choices available to students, certain characteristics of institutions can ameliorate or exacerbate these relationships. Indeed, researchers have found that the ecology of institutions and departments can have meaningful impacts on students' choice of major, including those with an interest STEM fields (Griffith, 2010). Others note that characteristics such as whether or not institutions have traditionally served Lationa/o or Black students can have a strong impact on STEM retention efforts (Crisp et al., 2009; Garcia & Hurtado, 2011). From a policy perspective, the institutional effects model is important because it assumes that IHEs can make changes to achieve desired outcomes even in the face of challenges from exogenous factors (e.g., differential familial socialization or high school preparation).

If the assumptions of the institutional effects literature are correct then it can be expected that institutional characteristics such as the degree of selectivity, doctoral and research activity, and designation as a Historically Black College and University (HBCU) or Hispanic Serving Institution (HSI) should be associated with a meaningful amount of change in the likelihood of switching from a STEM major to a non-STEM major—at least for certain students. This expectation is grounded in the idea that these characteristics point to proxies for the student body environment and the extent to which institutional resources are available to support undergraduate education (Eagan, Hurtado, & Chang, 2010).

Data and Methods

As noted, the data for this study came from the restricted version of the BPS:04/09 cohort conducted by the U.S. Department of Education. BPS:04/09 followed a cohort of students who were enrolling in postsecondary education for the first time at the end of their first academic year (2003-04). The original cohort came from the 2003-04 National Postsecondary Student Aid Study (NPSAS:04), which is a large, nationally representative sample of postsecondary students and institutions for student financial aid, and comprises 18,640 first-time beginning students (FTBs) at any postsecondary institution in the United States. They were followed up at the end of their third (2005-06) and sixth (2008-09) years after entry into postsecondary education and, finally, 16,680 FTBs were classified as BPS:04/09 respondents.

To look at FTB's major-switching patterns over 6 years in college, this study focused on a subsample of BPS:04/09 students who participated not only in the initial survey in 2003-04 but also in two follow-up surveys in 2006 and 2009. As a result of a series of selective processes, the 4-year college track presents different advantages, achievement levels, and aspirations relative to other postsecondary trajectories (Goldrick-Rab, 2006; Goldrick-Rab & Pfeffer, 2009). Our preliminary analysis indicated that college students who began their postsecondary education at 4-year institutions had not only different switching patterns but also different social and academic backgrounds compared to those at 2-year institutions. Thus, we restricted our sample to students who began their postsecondary education in a bachelor's degree program at a 4-year institution, which consisted of approximately 7,800 beginning bachelor's degree students. Further, we excluded (1) students who began their postsecondary education in an associate's degree program, (2) students who initially declared their major after their first year, and (3) students who had not enrolled in college since July 2006, assuming that they left postsecondary education. We assumed that students in each group are distinct not only in their social and academic background but also in their college experience, and thus left further analyses with these students for future study. These steps yielded a final sample of approximately 5,210 students. Finally, our preliminary analysis also showed that students beginning with STEM majors differed from those beginning with non-STEM majors in terms of their social and academic backgrounds. To reduce the amount of unobserved heterogeneity these two groups were analyzed separately.

Measures

In this study, five major fields are classified as STEM majors: mathematics, physical sciences, bio/life sciences, computer and information sciences, and engineering/technologies. Non-STEM majors consist of six broad fields: social/behavioral science, humanities, business, education, health science, and other fields. We recognize a degree of arbitrariness in defining these groups of majors in this way, and in doing so followed previous research and areas of emphasis in policy (see Chen, 2013). Based on this classification of majors, we identified FTB's switching patterns (1) from STEM majors into non-STEM majors, (2) from non-STEM majors into STEM majors, and (3) from non-STEM majors into other non-STEM majors, which are the dependent variables of central interest to our analysis. We compare each type of switchers to its own counterpart, non-switchers. In identifying switching patterns, we define an *origin major* as the first declared major during the first academic year (2003-04) and a *destination major* as the final major through 2009. Whereas some studies use intended major (e.g., as recorded through the SAT) to identify college students' switching patterns, we used their first declared major as the point of origin assuming it is a more realistic measure of students' actual switching patterns. Further, we defined *non-switchers* as students who stayed in their declared majors between origin and destination, and *switchers* as those who switched their declared majors into other major groups through 2009 at the end of their sixth year after entry into postsecondary education.[1] In cases where students attained their BA before 2009, we consider their major of BA degree as a destination major.

To test the social and cultural reproduction model of switching we focused on demographic and background characteristics of the students, which included gender and race[2] variables. Parental education was measured as the highest level of education by either parent, which was merged into a binary variable: "Bachelor's degree or more" and "less than 4 years of college." Family income indicated the Adjusted Gross Income (AGI) reported in 2002 and was transformed with a natural logarithm in the analysis. We also included measures of college

[1] A small portion of students initially moved their major to other major fields before switching back to their initial major fields. Because they finally stayed in their initial major fields, we considered these students as non-switchers. Whereas we found two different types of switching patterns, in which early switchers switched their major during early academic year and later switchers switched their major during their later academic year (i.e., before or after their third academic year in 2005-06), they were not distinguished in this analysis due to the small sample size.

[2] Our analysis uses five categories: Black, White, Hispanic, Asian, and a catch-all category for those who identify with alternative categories. We recognize that these categories miss important differences within groups and omit certain groups altogether (e.g., Native Americans). The survey design and sample sizes restrict our ability to examine these differences in the present analysis, but future studies should utilize datasets with more inclusive racial representations.

preparedness as proxies for accumulated cultural capital. These measures included (1) college admission test score (ACT or SAT), (2) high school GPA (A- or A), (3) highest level of high school math that students completed (Calculus), and (4) incoming college credits that students earned while they were in high school (Yes/No). Except for the admission test score, each measure was coded as a dummy.

For Tinto's theory of student departure we specified a series of measures regarding college experience. In particular, we included variables measuring academic integration in the first year: (1) the students' college GPA, (2) the proportion of STEM credits relative to all credits, (3) highest mathematics course taken, and (4) the STEM GPA compared to non-STEM GPA. In addition, as indictors of social integration during college life, a series of dummy variables (combining 'never' and 'sometimes' as a reference group) were included that measure whether or how often each of the following occurred during the first year: (1) attended large lecture classes, (2) had informal or social contact with faculty members outside of classrooms and the office, (3) talked with faculty about academic matters outside of class time (including email), (4) met with an advisor concerning academic plans, (5) attended study groups outside of the classroom, and (6) participated in school clubs.

For the rational choice model we focused on students' employment and financial situations: (1) whether or not students worked more than 10 hours per week during the first year of college, (2) the cumulative Stafford and Perkins loan amount they borrowed through 2006, (3) whether or how many years they received a Pell grant through 2006 (ranging from no Pell grant to 3 years), (4) expected family contribution, indicating the composite estimate of the federal Expected Family Contribution used in need analysis reported in 2003-04, (5) received help repaying loans, denoting whether anyone helped the student repay his/her undergraduate loans as of January 2009, and (6) the cost of attendance, indicating the price of attendance or total student budget. Cumulative Stafford and Perkins loan amount, expected family contribution, and cost of attendance were transformed with a natural logarithm in the analysis.

Finally, as measures of institutional characteristics we included (1) whether students attended, as their first institution, either a HBCU or a HSI during the 2003-04 academic year, (2) the level of selectivity of the first institution (very selective), and (3) whether they attended a doctoral-granting institution (research and doctoral institution) designated by the Basic Carnegie classification. To address the heterogeneity within fields of study we also took into account students' original field of study (see above) in the analysis of switching patterns in STEM and non-STEM fields. Descriptive statistics for all independent variables by switching pattern are presented in Appendix Table 1. More detailed descriptions of all independent variables are presented in Appendix Table 2.

Analytic Strategy

After a detailed descriptive analysis of switching majors we estimated a series of logistic regressions predicting whether a student switched his or her major (1) from STEM to non-STEM, (2) from non-STEM into STEM, and (3) from non-STEM into other non-STEM. Our first (baseline) model (M1) included the measures of social and cultural reproduction. In the second model (M2) we added the covariates that measure social and academic integration. The third model (M3) tests the measures specified by rational choice theory instead of social and academic integration. The fourth model (M4) includes the institutional characteristics, in addition to our baseline model (M1) to test institutional effects. Finally, we included all relevant covariates simultaneously (M5). Further sub-group analyses were then conducted for male and female subsamples to explore the gendered patterns of the models' explanatory power.

All analyses were weighted and adjusted to account for the complex survey design of the dataset using the STATA survey commands.[3] To handle missing information, we used a multiple imputation technique by chained equations in the STATA MI program (Morris, White, & Royston, 2014; Royston & White, 2011; White, Royston, & Wood, 2011). We created 40 complete datasets for the analysis (Graham, Olchowski, & Gilreath, 2007). Interactions and sub-group analysis were considered in the imputation process. While we present logit coefficients and their standard errors in tables, we also present the odds ratio, marginal effect, and average predicted probability for selected results. Finally, all unweighted sample entities were rounded to the nearest tenth for disclosure risks in this paper.

Results

Among FTBs who began their postsecondary education in a bachelor's degree program and initially declared a STEM major during the first academic year, 60.7% stayed in STEM majors while 39.3% switched their majors to non-STEM fields. Among all students majoring in a field other than STEM, 56.8% stayed in their respective field, 6.8% switched into a STEM major, and 36.4% moved into other non-STEM majors. Overall, women were more likely than men to switch out of their original STEM majors (44.5% vs. 36.8%, Figure 1a) and less likely to switch into STEM majors regardless of their original major (Figure 1b). We also found racial and ethnic differences in switching patterns (Figures 1c and 1d). Compared to White students (33.8%), for example, Asians (23.5%) were less likely to switch out of STEM, whereas Black and Hispanic students were more likely to leave these fields of study (47.9% and 45.0%, respectively). Among non-STEM students, those identifying as Asian were most likely to switch into STEM fields from health science (45.4%), humanities (13.9%), and education (4.9%), while Hispanic students were most likely to switch into STEM from business (10.1%), and White students (5.0%) were most likely to switch into STEM fields from social/behavioral science.

[3] We used the BPS:04/09 panel weight WTB000 to analyze study respondents for the base-year study (NPSAS:04), the first follow up (BPS:04/06), and the second follow up (BPS:04/09). The strata and PSU variables for variance estimation were BPS09STR and BPS09PSU, respectively (Wine et al., 2011).

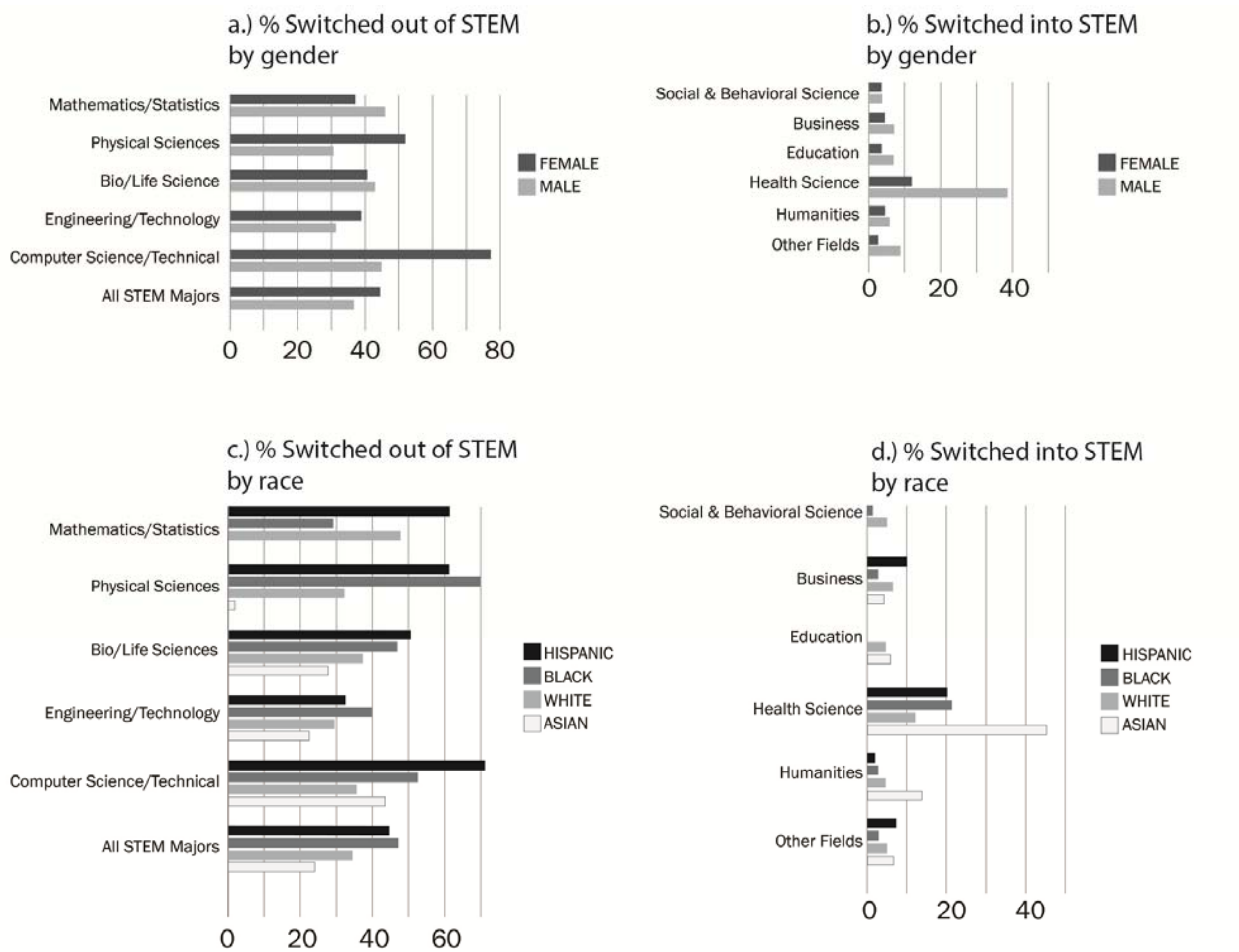

***Figure 1*. Patterns of Switching from and into STEM Majors by 2009 for Beginning Bachelor's Students by Gender and Race**

Note: Some racial groups had values of zero for certain switching patterns and thus do not have a bar.

The heterogeneity in switching patterns within the major groups of study is pervasive. In STEM fields, for instance, engineering/technologies (32.5%) showed a lower rate of switching out of STEM, while computer and information sciences (50.6%) showed a higher switching rate. Relative to other non-STEM fields, health science showed an approximately 3–5 times higher rate of switching into STEM, and humanities and education had relatively higher rates of switching into other non-STEM fields. Within these more specific patterns of switching we found additional gender and racial disparities. In particular, Figure 1a illustrates that women were more likely than men to switch from the male dominated majors of physical sciences (52.0% vs. 30.6%, respectively), engineering/technologies (38.9% vs. 31.3%), and computer and information sciences (77.2% vs. 44.9%), but were less likely to switch from female dominant majors in the bio/life sciences (40.7% vs. 42.9%).[4] Relative to women majoring in non-STEM

[4] In our sample, approximately 84% in engineering/technologies and 83% in computer and information sciences were men, whereas 56% in bio/life sciences and 66% in mathematics were women. While physical sciences are well known as

fields (Figure 2a), men switching into other non-STEM fields was less likely in business (28.6% vs. 37.6%), but more likely in education (61.4% vs. 44.3%). In health sciences, men were three times more likely than women to switch into STEM fields (38.8% vs. 12.2%). Black and Hispanic students were especially more likely than other groups to switch out of STEM in physical sciences and computer/information sciences (Figure 1c), and more likely to switch into other non-STEM fields from education (Figure 2b). Asian students, meanwhile, were more likely than other racial and ethnic groups to stay in business.

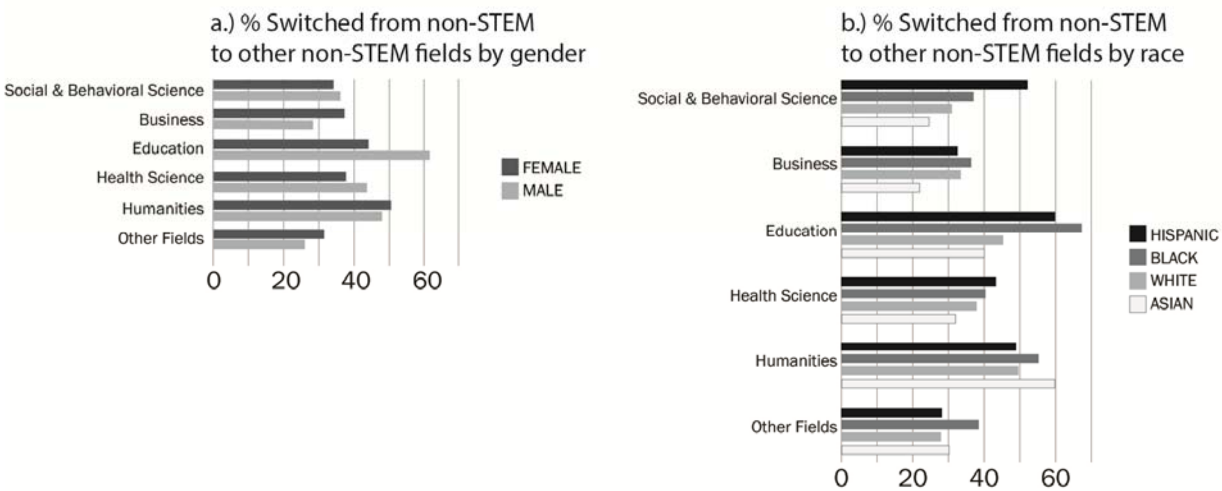

***Figure 2*. Patterns of Switching from non-STEM Majors by 2009 for Beginning Bachelor's Students by Gender and Race**

In addition to gender and race, descriptive analyses also suggest differences across social, economic, academic, and institutional patterns of switching out of and into a wide variety of majors. Compared to non-switchers across all fields, for example, switchers were somewhat disadvantaged in terms of their social, economic, and academic backgrounds and the types of institutions attended. For instance, STEM switchers had lower family socioeconomic status, were less prepared to study in college, less socially and academically integrated into college life, needed more financial support, and enrolled in less prestigious universities or colleges. However, switchers into STEM were rather advantaged over non-STEM switchers who moved into other non-STEM fields, and even slightly advantaged over non-switchers in non-STEM fields.

Switching Out of STEM Majors

We next report the results of blocked regressions to assess the extent to which the factors noted above are associated with students' switching patterns and to compare how well (or not) each theory accounts for changes in the likelihood of these patterns. Table 1 presents the results

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historically male-dominant STEM majors (National Science Board, 2004; Riegle-Crumb & King, 2010), only 52% of physical science majors in our sample were men. On average, 67% of STEM majors in our sample were men.

of the logistic regressions on college students' switching out of STEM majors. The baseline model (M1) indicated that students' demographic and family background variables did not significantly predict their switching from a STEM to non-STEM major. In fact, taking a calculus class in high school was the only significant predictor of change in the likelihood of switching (toward persistence), but it appears this association was mediated through students' college experience as evidenced in the social and academic integration (M2) and full (M5) models. Further, when accounting for college experiences in M2 the gender association became significant and was consistent in the full model. When accounting for all variables, the odds of switching out of a STEM major for women were 1.51 [=exp(0.410)] times higher than that of men.[5]

In the social and academic integration model (M2), achieving a higher college GPA and frequently engaging in study groups significantly predicted students' persistence in STEM fields, and taking a lower proportion of STEM credits in the first year significantly predicted switching out of these majors. These relationships were consistent even after accounting for all covariates in the full model, which supports the theory that a greater degree of academic and social integration reduces the likelihood of switching out of STEM disciplines. In the rational choice model (M3), working more than 10 hours per week and lower cost of attendance significantly predicted STEM students' switching to non-STEM majors. However, these associations disappeared in M5 when considering all other covariates. Whereas institutional characteristics were not significantly associated with switching out of STEM in the institutional effects model (M4), attending a doctoral-granting institution became significant in predicting students' switching out of STEM after accounting for all covariates in the full model.

There is also evidence that the differences in switching across the different STEM majors persist even when accounting for all of the covariates in the analysis. Most notably, Table 1 confirms that in the full model students in engineering/technologies were significantly less likely to switch out of STEM fields than those in physical sciences. In fact, the odds of switching out of STEM for students in physical sciences were 2.1 [=exp(0.729)] times higher than that of their counterparts in engineering/technologies.[6] In M1, M3, and M4 computer and information science majors were more likely to switch out of STEM than those in engineering/technologies, but the association was not significant in the full model.

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[5] Its average marginal effect is 0.099 and thus this is approximately 10% of difference between male and female (average predicted probability is 54% for male and 64% for female).

[6] This is an approximately 9.6% of difference in probability of switching out of STEM fields between these two majors, which is quite similar with the descriptive statistics (40.9% in physical sciences and 32.5% in engineering/technologies).

Table 1. **Summary Results from Logistic Regression of STEM Students' Switching Major out of STEM Fields on their Demographic, Family Background, College Preparedness, College Experience, Financial Support, and Institutional Characteristics (N = 1,260)**

Variables	M1	M2	M3	M4	M5
Female	0.256	0.419*	0.232	0.267	0.410*
	(0.161)	(0.176)	(0.161)	(0.161)	(0.178)
Black	0.264	0.329	0.404	0.158	0.247
	(0.269)	(0.259)	(0.282)	(0.305)	(0.334)
Hispanic	0.111	0.169	0.046	-0.002	-0.105
	(0.337)	(0.328)	(0.332)	(0.299)	(0.326)
Asian	-0.559	-0.433	-0.472	-0.605	-0.456
	(0.316)	(0.321)	(0.329)	(0.322)	(0.325)
Parents' Education (BA or more)	-0.142	-0.168	-0.098	-0.152	-0.136
	(0.175)	(0.190)	(0.174)	(0.177)	(0.192)
Income (log)	0.006	-0.005	0.024	0.002	0.070
	(0.065)	(0.067)	(0.074)	(0.063)	(0.093)
College Admission Test Score (ACT or SAT)	-0.071	0.047	-0.036	-0.082	0.055
	(0.056)	(0.061)	(0.055)	(0.061)	(0.062)
High School GPA (3.5~4.0; A- to A)	-0.192	0.037	-0.208	-0.225	-0.029
	(0.169)	(0.179)	(0.167)	(0.169)	(0.179)
Highest level of High School Math (Calculus)	-0.576**	-0.270	-0.494*	-0.592**	-0.246
	(0.200)	(0.202)	(0.219)	(0.198)	(0.216)
Incoming College Credits	-0.114	0.006	-0.080	-0.115	0.059
	(0.160)	(0.181)	(0.163)	(0.162)	(0.182)
College GPA, 2004		-0.726***			-0.725***
		(0.136)			(0.139)
Percent of STEM credits in all credits earned in first year (ref. 50 percent or higher)					
Lower than 25 percent		1.776***			1.837***
		(0.331)			(0.330)
25-49 percent		0.980***			1.040***
		(0.212)			(0.212)
Highest mathematics in first year (ref. Calculus/advanced math)					
No math		0.351			0.327
		(0.240)			(0.259)
Precollege-level math		0.792			0.685
		(0.468)			(0.460)
Introductory math		0.320			0.291
		(0.261)			(0.269)
STEM GPA compared to non-STEM GPA in first year (ref. About the same or higher)					
Lower by at least 1.0 grade point		0.217			0.214
		(0.293)			(0.305)
Lower by 0.5 to 0.9 grade point		0.358			0.332
		(0.214)			(0.221)

Table 1, **continued. Summary Results from Logistic Regression of STEM Students' Switching Major out of STEM Fields on their Demographic, Family Background, College Preparedness, College Experience, Financial Support, and Institutional Characteristics (N = 1,260)**

Variables	M1	M2	M3	M4	M5
Social Integration (often; ref. none & sometimes)					
Large classes, 2004		0.021			-0.124
		(0.161)			(0.162)
Informal meeting with faculty, 2004		-0.487			-0.468
		(0.310)			(0.317)
Talking to faculty outside of class, 2004		0.019			0.025
		(0.246)			(0.240)
Meeting with academic advisor, 2004		-0.187			-0.171
		(0.222)			(0.215)
Study groups, 2004		-0.468*			-0.459*
		(0.197)			(0.195)
Clubs, 2004		0.146			0.216
		(0.200)			(0.206)
Cumulative Federal Student Loan through 2006 (log)			-0.032		-0.039
			(0.034)		(0.036)
Pell grant: number of years received, 2006 (ref. none)					
One ~ Two			0.095		0.095
			(0.237)		(0.272)
Three			0.171		0.335
			(0.278)		(0.340)
Working more than 10hrs per week, 2004			0.330*		0.311
			(0.155)		(0.169)
Expected family contribution, 2004 (log)			0.010		-0.018
			(0.029)		(0.036)
Receiving help repaying loans			0.398		0.305
			(0.355)		(0.375)
Cost of attendance (log)			-0.534*		-0.384
			(0.223)		(0.239)
HBCU & HIS				0.195	0.271
				(0.338)	(0.377)
First Institution selectivity, 04yr (Very selective: ref. Others)				0.021	0.119
				(0.224)	(0.208)
Doctoral-granting Institution (Research & Doctoral)				0.250	0.388*
				(0.192)	(0.194)
Fields of Study (ref. Engineering/Technologies)					
Bio/life Sciences	0.292	0.246	0.329	0.311	0.331
	(0.206)	(0.257)	(0.219)	(0.208)	(0.278)
Physical Sciences	0.428	0.668	0.408	0.491	0.729*
	(0.348)	(0.347)	(0.365)	(0.343)	(0.358)
Mathematics	0.628	0.377	0.674	0.667	0.461
	(0.346)	(0.483)	(0.359)	(0.350)	(0.496)
Computer and Information Sciences	0.552*	0.431	0.527*	0.606**	0.485
	(0.229)	(0.277)	(0.238)	(0.225)	(0.288)

Notes. * p<0.05, **p<0.01, *** p<0.001.

Switching Into STEM Majors

In Figure 2 we saw that switching into STEM from non-STEM fields was a relatively infrequent occurrence (6.8% overall). Table 2 presents the results of the logistic regressions on college students' switching into STEM majors from non-STEM fields. The social and cultural reproduction model (M1) indicated that women were significantly less likely to move into STEM fields, a finding that was consistent through all models, though its effect was slightly reduced in the full model. Indeed, in the full model the odds of switching into STEM fields for men were 2.43 [=1/exp(-0.886)] times higher than that of women.[7] M1 also shows that taking a calculus class in high school significantly increased the likelihood of switching into STEM, and was also consistent through the full model. Asian students were significantly more likely to switch into STEM than White students, although the significance disappeared when controlling for all covariates in the full model. Finally, income was significant in the full model even though it was not the case in M1 through M4. Interestingly, lower income levels *increased* the likelihood of switching into STEM from non-STEM fields.[8]

The social and academic integration model (M2) highlights the importance of STEM coursetaking in the first year of college. Even though overall GPA and STEM GPA were not significant, taking a higher proportion of STEM credits and taking a calculus or advanced math course during the first year significantly increased the likelihood of switching into STEM fields. Whereas none of the variables regarding financial support (M3) and institutional characteristics (M4) were significant, the higher cost of attendance and attending a doctoral-granting institution did significantly predict students' persistence in non-STEM fields after controlling for all covariates in the full model. Not surprisingly, students in health sciences were also most likely to switch into STEM in the full model, with odds 4.1 [=exp(1.422)] times higher than that of students in the social/behavior sciences.[9]

[7] Average predicted probability is approximately 12% for male and 5% for female and thus its difference is around 7%.

[8] It is worth noting that the p-value on this income predictor is close to the margin of 0.05 significance level and somewhat sensitive to model specifications and multiple imputation (i.e., the number of datasets).

[9] Average predicted probability for students in health sciences is approximately 22% whereas those probabilities for other non-STEM majors are below 10%.

Table 2. **Summary Results from Logistic Regression of Non-STEM Students' Switching Major into STEM Fields on their Demographic, Family Background, College Preparedness, College Experience, Financial Support, and Institutional Characteristics (N = 2,550)**

Variables	M1	M2	M3	M4	M5
Female	-1.043***	-0.905**	-1.038***	-1.047***	-0.886**
	(0.244)	(0.279)	(0.240)	(0.244)	(0.277)
Black	-0.042	-0.187	0.052	-0.136	-0.030
	(0.364)	(0.425)	(0.375)	(0.323)	(0.394)
Hispanic	0.350	0.277	0.379	0.250	0.325
	(0.284)	(0.301)	(0.281)	(0.323)	(0.345)
Asian	0.557*	0.291	0.663**	0.490	0.460
	(0.240)	(0.258)	(0.250)	(0.251)	(0.279)
Parents' Education (BA or more)	0.246	0.113	0.224	0.227	0.116
	(0.187)	(0.193)	(0.194)	(0.187)	(0.199)
Income (log)	-0.072	-0.096	-0.175	-0.069	-0.217*
	(0.094)	(0.097)	(0.113)	(0.090)	(0.110)
College Admission Test Score (ACT or SAT)	0.011	-0.043	0.019	0.008	-0.026
	(0.070)	(0.079)	(0.072)	(0.074)	(0.082)
High School GPA (3.5~4.0; A- to A)	0.176	0.105	0.185	0.159	0.124
	(0.186)	(0.204)	(0.182)	(0.188)	(0.200)
Highest level of High School Math (Calculus)	0.759***	0.636***	0.767***	0.735***	0.693***
	(0.166)	(0.179)	(0.167)	(0.165)	(0.181)
Incoming College Credits	-0.238	-0.277	-0.280	-0.269	-0.304
	(0.201)	(0.196)	(0.211)	(0.204)	(0.202)
College GPA, 2004		-0.159			-0.161
		(0.129)			(0.131)
Percent of STEM credits in all credits earned in first year (ref. 50 percent or higher)					
Lower than 25 percent		-1.981***			-2.010***
		(0.300)			(0.299)
25-49 percent		-0.967***			-0.986***
		(0.253)			(0.261)
Highest mathematics in first year (ref. Calculus/advanced math)					
No math		-0.617*			-0.672*
		(0.258)			(0.265)
Precollege-level math		-1.040**			-1.124**
		(0.374)			(0.387)
Introductory math		-0.834***			-0.896***
		(0.230)			(0.234)
STEM GPA compared to non-STEM GPA in first year (ref. About the same or higher)					
Lower by at least 1.0 grade point		-0.163			-0.104
		(0.259)			(0.272)
Lower by 0.5 to 0.9 grade point		-0.078			-0.023
		(0.231)			(0.232)

***Table 2*, continued. Summary Results from Logistic Regression of Non-STEM Students' Switching Major into STEM Fields on their Demographic, Family Background, College Preparedness, College Experience, Financial Support, and Institutional Characteristics (N = 2,550)**

Variables	M1	M2	M3	M4	M5
Social Integration (often; ref. none & sometimes)					
Large classes, 2004		0.007			0.058
		(0.201)			(0.214)
Informal meeting with faculty, 2004		0.427			0.456
		(0.270)			(0.271)
Talking to faculty outside of class, 2004		-0.014			0.040
		(0.235)			(0.241)
Meeting with academic advisor, 2004		0.201			0.236
		(0.212)			(0.217)
Study groups, 2004		0.256			0.314
		(0.231)			(0.235)
Clubs, 2004		-0.144			-0.125
		(0.216)			(0.214)
Cumulative Federal Student Loan through 2006 (log)			-0.011		-0.011
			(0.040)		(0.043)
Pell grant: number of years received, 2006 (ref. none)					
One ~ Two			0.126		0.142
			(0.230)		(0.245)
Three			0.028		-0.039
			(0.310)		(0.341)
Working more than 10hrs per week, 2004			-0.136		-0.154
			(0.166)		(0.171)
Expected family contribution, 2004 (log)			0.072		0.082
			(0.042)		(0.043)
Receiving help repaying loans			-0.460		-0.177
			(0.358)		(0.373)
Cost of attendance (log)			-0.302		-0.449*
			(0.199)		(0.208)
HBCU & HIS				0.264	-0.016
				(0.328)	(0.385)
First Institution selectivity, 04yr (Very selective: ref. Others)				0.353	0.155
				(0.227)	(0.244)
Doctoral-granting Institution (Research & Doctoral)				-0.092	-0.436*
				(0.203)	(0.212)
Fields of Study (ref. Social/Behavioral Sciences)					
Humanities	0.644	0.704	0.678	0.649	0.717
	(0.506)	(0.511)	(0.501)	(0.516)	(0.511)
Business	0.369	0.182	0.343	0.397	0.174
	(0.382)	(0.385)	(0.380)	(0.385)	(0.378)
Education	0.709	0.753	0.676	0.734	0.682
	(0.518)	(0.515)	(0.517)	(0.532)	(0.523)
Health Science	2.163***	1.428**	2.112***	2.218***	1.422**
	(0.448)	(0.440)	(0.445)	(0.461)	(0.440)
Others	0.294	0.327	0.302	0.307	0.337
	(0.428)	(0.417)	(0.429)	(0.435)	(0.420)

Notes. * p<0.05, **p<0.01, *** p<0.001.

Switching Majors Within Non-STEM Fields of Study

A key question in this analysis is whether or not the social and cultural inequality observed in STEM switching patterns is observable in other areas of study. With all the attention being paid to the experiences of underrepresented students in STEM fields, one must wonder whether these patterns are in fact found in other fields of study as well. The models in Table 3 speak directly to this question, as they represent non-STEM students' switching into other non-STEM majors. Unlike students' switching out of and into majors in STEM fields, the social and cultural reproduction model (M1) showed that there was no significant gender disparity in switching from majors non-STEM fields into other non-STEM fields—with a gap that was almost zero in the full model. Economic constraints in the family, on the other hand, actually increased non-STEM students' persistence in their origin major in that lower family income decreased the likelihood of switching majors within non-STEM fields, a finding that is consistent in the full model as well.

Whereas lower college admission test scores also significantly increased the likelihood of switching majors within non-STEM fields, its effect seemed to be mediated through college GPA and consequently its significance disappeared in M2 and M5. As with non-STEM students' switching into STEM, the higher cost of attendance significantly reduced the likelihood of these students switching to majors in other non-STEM fields (see M3 and M5). However, institutional characteristics neither increased nor reduced the likelihood of switching majors within these fields. As anticipated in Figure 2, students in the humanities and education were relatively more likely to switch majors into other non-STEM fields while those in business and "other majors" were less likely to switch.

***Table 3*. Summary Results from Logistic Regression of Non-STEM Students' Switching Major into Other Non-STEM Fields on their Demographic, Family Background, College Preparedness, College Experience, Financial Support, and Institutional Characteristics (N = 3,680)**

Variables	M1	M2	M3	M4	M5
Female	-0.059	0.003	-0.052	-0.064	0.001
	(0.098)	(0.099)	(0.098)	(0.099)	(0.099)
Black	0.052	0.027	0.152	-0.002	0.079
	(0.159)	(0.164)	(0.160)	(0.160)	(0.165)
Hispanic	0.128	0.094	0.157	0.091	0.102
	(0.176)	(0.179)	(0.169)	(0.185)	(0.188)
Asian	-0.034	-0.072	0.039	-0.065	-0.016
	(0.218)	(0.219)	(0.216)	(0.217)	(0.218)
Parents' Education (BA or more)	0.007	-0.009	-0.006	-0.005	-0.035
	(0.094)	(0.094)	(0.097)	(0.094)	(0.099)
Income (log)	-0.074*	-0.075*	-0.135**	-0.076*	-0.143**
	(0.036)	(0.036)	(0.047)	(0.037)	(0.047)
College Admission Test Score (ACT or SAT)	-0.071*	-0.052	-0.071*	-0.083*	-0.064
	(0.032)	(0.034)	(0.034)	(0.034)	(0.037)
High School GPA (3.5~4.0; A- to A)	-0.110	-0.033	-0.100	-0.119	-0.037
	(0.099)	(0.101)	(0.100)	(0.099)	(0.101)
Highest level of High School Math (Calculus)	-0.170	-0.140	-0.154	-0.185	-0.139
	(0.115)	(0.116)	(0.114)	(0.115)	(0.116)
Incoming College Credits	0.006	0.029	-0.004	-0.007	0.006
	(0.102)	(0.104)	(0.105)	(0.102)	(0.106)
College GPA, 2004		-0.299***			-0.286***
		(0.060)			(0.061)
Social Integration (often; ref. none & sometimes)					
Large classes, 2004		0.085			0.034
		(0.089)			(0.101)
Informal meeting with faculty, 2004		0.090			0.134
		(0.159)			(0.159)
Talking to faculty outside of class, 2004		-0.239			-0.238
		(0.123)			(0.123)
Meeting with academic advisor, 2004		0.017			0.040
		(0.109)			(0.108)
Study groups, 2004		0.058			0.074
		(0.126)			(0.128)
Clubs, 2004		0.015			0.042
		(0.120)			(0.119)

***Table 3*, continued. Summary Results from Logistic Regression of Non-STEM Students' Switching Major into Other Non-STEM Fields on their Demographic, Family Background, College Preparedness, College Experience, Financial Support, and Institutional Characteristics (N = 3,680)**

Variables	M1	M2	M3	M4	M5
Cumulative Federal Student Loan through 2006 (log)			0.002		0.002
			(0.021)		(0.021)
Pell grant: number of years received, 2006 (ref. none)					
One ~ Two			0.004		0.023
			(0.126)		(0.130)
Three			-0.301		-0.258
			(0.162)		(0.163)
Working more than 10hrs per week, 2004			0.012		0.013
			(0.084)		(0.087)
Expected family contribution, 2004 (log)			0.027		0.032
			(0.020)		(0.021)
Receiving help repaying loans			-0.102		-0.116
			(0.174)		(0.177)
Cost of attendance (log)			-0.256*		-0.253*
			(0.114)		(0.116)
HBCU & HIS				0.043	0.013
				(0.183)	(0.173)
First Institution selectivity, 04yr (Very selective: ref. Others)				0.120	0.170
				(0.122)	(0.122)
Doctoral-granting Institution (Research & Doctoral)				0.087	0.039
				(0.092)	(0.100)
Fields of Study (ref. Social/Behavioral Sciences)					
Humanities	0.731***	0.756***	0.744***	0.746***	0.782***
	(0.202)	(0.202)	(0.201)	(0.202)	(0.201)
Business	-0.089	-0.093	-0.112	-0.082	-0.102
	(0.144)	(0.146)	(0.146)	(0.144)	(0.148)
Education	0.551***	0.544***	0.516***	0.572***	0.533***
	(0.142)	(0.145)	(0.142)	(0.145)	(0.146)
Health Science	0.418**	0.364*	0.376*	0.423**	0.354*
	(0.156)	(0.157)	(0.158)	(0.161)	(0.161)
Others	-0.285*	-0.313*	-0.295*	-0.271	-0.301*
	(0.139)	(0.141)	(0.138)	(0.139)	(0.140)

Notes. * p<0.05, **p<0.01, *** p<0.001.

Gender Subgroup Analysis

We conclude our analysis by exploring differences across gender subgroups relative to the three switching trajectories (out of STEM, into STEM, and non-STEM to non-STEM, see Table 4). Among men switching out of STEM (M1), college preparedness and academic integration (college GPA, STEM credits, and STEM GPA) were key factors associated with their decision to switch majors. In particular, men majoring in STEM whose STEM GPA was 0.5 to 0.9 points lower than their non-STEM GPA were significantly more likely than women to leave STEM fields.[10] For women (M2), on the other hand, participating in study groups, working more than 10 hours per week, and attending a doctoral-granting institution had significant impacts on their decision to switch out of STEM or not. For women, a greater degree of social integration reduced the likelihood of switching out of STEM, while financial and institutional constraints hindered their persistence in these majors. As anticipated in the descriptive analysis, there are also key gender differences with respect to the specific STEM discipline. Whereas the likelihood of switching out of STEM did not differ across the fields of study for men, women in computer and information sciences were significantly more likely to leave for non-STEM majors than those in engineering/technologies.

There are also important gender differences among those switching into STEM majors (M3 and M4). For instance, among men, lower family income and frequently participating in large classes *increased* the likelihood of switching into STEM. On the other hand, participation in study groups increased the likelihood of staying in STEM among women (see M2). In addition, taking a calculus/ advanced math course in the first year of college was more important among women switching into STEM, while the higher cost of attendance decreased the likelihood of women making this switch (i.e., persisting in a non-STEM field). Neither relationship was observed among men in the sample.

Perhaps the most unexpected findings in the subgroup analysis were the significant racial associations that move in opposite directions across the subsamples of men and women. Whereas Black men were much less likely to switch into STEM than White men, Black women were more likely to switch into STEM majors than White women and even significantly more likely than Black men. This is opposite to the fact that, on average, women were less likely to switch into STEM than men (see Figure 1b). In contrast, Black women were significantly more likely to switch out of STEM than their male counterparts, which is consistent with the fact that, on average, women were more likely than men to switch out of STEM.[11] In short, Black women were more likely to switch into STEM majors, but they were also more likely to switch out.

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[10] In multiple-datasets there are some computational difficulties to test the difference of coefficients between subgroups. Thus, in this section, we indirectly test its difference by examining interaction terms in a pooled sample. Test statistics are not reported in this paper but will be provided upon request.

[11] In M1 and M2, the Black category was not significantly associated with switching out of STEM in both male and female subsamples. However, the interaction between Black and gender was statistically significant ($p<0.05$; not reported here), which indicated Black females were significantly more likely to switch out of STEM than Black males. While we suggest that this finding is informative, it requires further scrutiny because the sample size of Black students, particularly, who switched into STEM is very small in our analysis.

Table 4. **Summary Results from Logistic Regression of Switching out of STEM Majors, Switching into STEM Majors, and Switching into Other Non-STEM Majors by Gender**

	Out of STEM (vs. STEM persistence)		Into STEM (vs. Non-STEM persistence)		Switching Major within Non-STEM fields (vs. Non-STEM persistence)	
	Male	Female	Male	Female	Male	Female
Variables	M1	M2	M3	M4	M5	M6
Black	-0.200	0.597	-3.065**	0.849*	0.118	0.038
	(0.547)	(0.434)	(1.060)	(0.413)	(0.305)	(0.189)
Hispanic	-0.375	0.273	0.769	0.168	0.342	-0.051
	(0.424)	(0.488)	(0.469)	(0.503)	(0.321)	(0.229)
Asian	-0.221	-1.175	0.459	0.486	-0.043	-0.021
	(0.394)	(0.653)	(0.491)	(0.376)	(0.355)	(0.265)
Parents' Education (BA or more)	-0.276	-0.125	0.165	0.055	-0.085	-0.004
	(0.244)	(0.279)	(0.325)	(0.274)	(0.174)	(0.120)
Income (log)	0.005	0.263	-0.311*	-0.158	-0.193**	-0.123*
	(0.121)	(0.149)	(0.151)	(0.119)	(0.074)	(0.057)
College Admission Test Score (ACT or SAT)	0.125	0.005	-0.246	0.094	-0.130	-0.027
	(0.083)	(0.132)	(0.140)	(0.096)	(0.066)	(0.044)
High School GPA (3.5~4.0; A- to A)	-0.104	0.207	0.199	0.028	0.135	-0.125
	(0.228)	(0.381)	(0.332)	(0.246)	(0.193)	(0.123)
Highest level of High School Math (Calculus)	-0.461	-0.116	0.668*	0.770**	-0.085	-0.151
	(0.257)	(0.359)	(0.280)	(0.264)	(0.225)	(0.137)
Incoming College Credits	0.386	-0.460	-0.232	-0.223	0.080	-0.019
	(0.228)	(0.329)	(0.341)	(0.247)	(0.193)	(0.119)
College GPA, 2004	-0.752***	-0.743*	-0.025	-0.252	-0.247*	-0.328***
	(0.158)	(0.320)	(0.170)	(0.195)	(0.109)	(0.081)
Percent of STEM credits in all credits earned in first year (ref. 50 percent or higher)						
Lower than 25 percent	2.184***	1.861**	-2.790***	-1.666***		
	(0.385)	(0.598)	(0.518)	(0.387)		
25-49 percent	1.303***	0.792*	-1.345**	-0.866**		
	(0.263)	(0.355)	(0.480)	(0.297)		
Highest mathematics in first year (ref. Calculus/advanced math)						
No math	0.276	0.429	0.352	-1.367***		
	(0.352)	(0.469)	(0.437)	(0.362)		
Precollege-level math	0.379	1.051	-0.656	-1.359**		
	(0.552)	(0.965)	(0.622)	(0.523)		
Introductory math	0.200	0.609	-0.277	-1.304***		
	(0.340)	(0.459)	(0.423)	(0.293)		
STEM GPA compared to non-STEM GPA in first year (ref. About the same or higher)						
Lower by at least 1.0 grade point	-0.041	0.818	-0.590	0.267		
	(0.353)	(0.443)	(0.493)	(0.348)		
Lower by 0.5 to 0.9 grade point	0.598*	-0.167	-0.015	-0.089		
	(0.294)	(0.377)	(0.416)	(0.297)		
Social Integration (often; ref. none & sometimes)						
Large classes, 2004	0.023	-0.400	0.761*	-0.211	0.123	-0.021
	(0.198)	(0.321)	(0.320)	(0.252)	(0.165)	(0.121)
Informal meeting with faculty, 2004	-0.687	-0.276	0.767	0.296	0.031	0.147
	(0.418)	(0.695)	(0.392)	(0.410)	(0.259)	(0.205)
Talking to faculty outside of class, 2004	0.176	-0.313	0.350	-0.205	-0.359	-0.183
	(0.325)	(0.462)	(0.328)	(0.341)	(0.242)	(0.137)
Meeting with academic advisor, 2004	-0.075	0.031	0.008	0.500	0.182	-0.024
	(0.275)	(0.406)	(0.350)	(0.277)	(0.212)	(0.129)
Study groups, 2004	-0.272	-0.906*	0.758	0.241	0.146	0.037
	(0.246)	(0.366)	(0.405)	(0.296)	(0.242)	(0.152)

Table 4, **continued. Summary Results from Logistic Regression of Switching out of STEM Majors, Switching into STEM Majors, and Switching into Other Non-STEM Majors by Gender**

	Out of STEM (vs. STEM persistence)		Into STEM (vs. Non-STEM persistence)		Switching Major within Non-STEM fields (vs. Non-STEM persistence)	
	Male	Female	Male	Female	Male	Female
Variables	M1	M2	M3	M4	M5	M6
Clubs, 2004	0.006	0.592	-0.550	-0.038	-0.189	0.114
	(0.256)	(0.393)	(0.355)	(0.297)	(0.202)	(0.143)
Cumulative Federal Student Loan through 2006 (log)	-0.055	0.012	-0.031	0.001	0.016	-0.005
	(0.044)	(0.055)	(0.064)	(0.059)	(0.038)	(0.024)
Pell grant: number of years received, 2006 (ref. none)						
One ~ Two	0.230	-0.167	0.507	-0.139	-0.162	0.080
	(0.338)	(0.479)	(0.427)	(0.312)	(0.257)	(0.152)
Three	0.118	0.994	-0.041	0.106	-0.287	-0.218
	(0.464)	(0.548)	(0.730)	(0.386)	(0.294)	(0.214)
Working more than 10hrs per week, 2004	0.072	0.788*	-0.115	-0.179	-0.095	0.068
	(0.204)	(0.302)	(0.313)	(0.238)	(0.159)	(0.112)
Expected family contribution, 2004 (log)	0.003	-0.055	0.121	0.069	0.060	0.023
	(0.043)	(0.064)	(0.071)	(0.048)	(0.041)	(0.025)
Receiving help repaying loans	0.055	0.646	-0.935	0.188	-0.527	0.051
	(0.474)	(0.623)	(0.608)	(0.487)	(0.383)	(0.205)
Cost of attendance (log)	-0.384	-0.370	-0.156	-0.687*	-0.060	-0.362*
	(0.290)	(0.386)	(0.325)	(0.329)	(0.189)	(0.143)
HBCU & HIS	0.457	0.187	-1.119	0.329	-0.045	0.029
	(0.597)	(0.441)	(0.723)	(0.452)	(0.319)	(0.200)
First Institution selectivity, 04yr (Very selective: ref. Others)	0.192	0.204	0.191	0.103	0.157	0.172
	(0.289)	(0.343)	(0.343)	(0.281)	(0.236)	(0.132)
Doctoral-granting Institution (Research & Doctoral)	0.363	0.670*	-0.398	-0.369	-0.054	0.088
	(0.256)	(0.275)	(0.345)	(0.265)	(0.194)	(0.117)
Fields of Study (ref. Engineering/Technologies; Social/Behavioral Sciences)						
Bio/life Sciences	0.437	0.510				
	(0.339)	(0.385)				
Physical Sciences	0.543	1.118				
	(0.476)	(0.570)				
Mathematics	0.531	0.973				
	(0.641)	(0.664)				
Computer and Information Sciences	0.326	1.652*				
	(0.320)	(0.648)				
Humanities			1.339	0.528	0.726	0.830***
			(0.726)	(0.674)	(0.389)	(0.233)
Business			0.819	-0.026	-0.391	0.107
			(0.500)	(0.495)	(0.259)	(0.182)
Education			1.966***	0.106	1.109***	0.431*
			(0.563)	(0.660)	(0.329)	(0.184)
Health Science			3.457***	0.883	1.213**	0.245
			(0.683)	(0.525)	(0.432)	(0.171)
Others			1.318**	-0.458	-0.529*	-0.170
			(0.473)	(0.579)	(0.266)	(0.164)
N	820	440	930	1610	1270	2410

Notes. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Finally, the most important differences to emerge from the gender subgroup analysis of non-STEM majors relates to the specific majors from which men and women switch. For example, men originally declaring a major in health sciences or education were more likely to switch to other non-STEM fields, while those in business were less likely to do so than men in other non-STEM majors (see M5). Meanwhile, women were more likely to switch from majors in the humanities to other non-STEM majors, and while they were significantly likely to switch from education they were less likely to do so than men (see M6). As with the whole group analysis (see Table 3), the only factors significantly associated with men and women switching between non-STEM majors were family income and college GPA; in both cases the association was negative (i.e., less likely to switch). The only observed difference across the gender subgroups was that the higher cost of attendance significantly increased the likelihood of women staying in non-STEM fields (see M6). Thus, from both the whole sample and subgroup analyses we can see that gender plays a key role in switching in and out of STEM majors net a wide variety of covariates, a finding that appears to be unique relative to majors in the humanities, education, social/behavior science, health sciences, and business.

Discussion and Conclusion

In this paper we set out to understand if social inequalities emerge through patterns of switching majors across a range of disciplines. Our primary objectives were to test theoretical models of switching STEM majors to better understand if social inequalities exist after accounting for a range of factors known to influence these patterns, and to compare these findings with those of non-STEM fields of study. Even though switching majors is not inherently problematic (in may even be desirable), the findings from our analysis suggest that we should, indeed, still be "talking about leaving" STEM majors. The gender, race, and class-based disparities in these patterns—not found in other majors—indicate that the high-status positions of STEM fields are sites of ongoing struggles for proponents of equity in higher education. These horizontal inequalities demonstrate that simply increasing the number of underrepresented groups declaring STEM majors is not, by itself, a sufficient means to achieving attainment parity.

One overarching theoretical insight derived from our analysis is that switching majors is a phenomenon that cuts across social, cultural, economic, and institutional contexts.[12] While our results suggest unique gendered and raced patterns of switching majors in STEM fields, choices related to financial concerns (e.g., family income, cost of attendance) appear relevant to students across all majors. Further, it appears to be crucial for STEM majors to be academically integrated into the curriculum in the first year, especially in relation to STEM coursetaking and performance in those courses. While prior research has examined the forms of social integration and cultural differentiation that take place through math and science coursetaking at the high school level (Frank et al., 2008; Legewie & DiPrete, 2014), researchers should further extend

[12] Although not tested in this analysis, the literature has firmly established that social psychological models shape these processes as well (Eccles 2007). Unfortunately the BPS dataset does not include these measures.

this work into the realm of higher education. In particular, it may be productive to test whether pedagogical practices in STEM courses interact with gendered and raced expectations of learning experiences and interactions, and if variations in gender and racial representations in STEM classrooms further shape these experiences.

A more specific theoretical insight emerging from our analysis is that the cultural reproduction of gender inequality in this context appears to work through forms of social integration, financial considerations, and institutional characteristics. Not only were females more likely to switch out of STEM majors (and less likely to switch into them) net academic preparation and performance, but these decisions were also associated with the need to work more than 10 hours per week and attendance at doctoral-granting research institutions. On the other hand, social integration emerging through practices such as study groups significantly changes this pattern toward persistence. These findings run counter to those of Gayles and Ampaw (2014), who found that participation in study groups is associated with a decreased likelihood of degree completion in STEM majors. It is possible that participation in study groups has different implications for women switching majors than it does completing degrees. Either way, the findings point to the important ways that gender and class relations work through features of the social and institutional environment to change the likelihood that women switch in and out of STEM majors. Future studies should take an in-depth look at these social and institutional contexts to better understand how they shape women's decisions to pursue majors in these fields.

The cultural reproduction of racial inequality in STEM switching patterns appears to work most pervasively through inequalities in high school experiences and postsecondary preparation—a finding that is consistent with prior qualitative research (Seymour & Hewitt, 1997). However, our analysis does (cautiously) suggest that gender and race interactions can play an important role once the student reaches the undergraduate level. Most notably, Black women were more likely to switch into STEM while also appearing to be more likely to switch out. Black men, on the other hand, are significantly less likely to switch not only into but also out of STEM majors. In fact, Black men are more likely to stay in either STEM or non-STEM fields than their female counterparts. While the large standard errors and small sample size of Black students, especially Black women, does not allow us to conclude the association between gender and race is an enduring one, these findings warrant additional scrutiny with datasets large enough to yield robust results. Prior research focusing on women of color suggests that a combination of social, cultural, and institutional relations are at work here, and that microanalyses of STEM classrooms may also add insights into these patterns (Ong et al., 2012).

Each of the theoretical models produced important insights with respect to switching into and out of STEM majors. Indeed, the theories of reproduction, integration, rational choice, and institutional effects each predicted meaningful changes in these outcomes. Yet, the findings point to a need for further theoretical development and synthesis to better account for the ways in which social and cultural reproduction in STEM fields takes place through the intersections of cultural capital accumulation at the secondary level, forms of social and academic integration at the undergraduate level, as well as financial considerations and the social organization of IHEs. In particular, gendered, raced and classed forms appear to inhere in the social relations of majors and organizational features of IHEs, and thus may be differentially activated through these intersecting processes. While the existing literature has made great progress toward understanding some of these processes independently, there remain large gaps across disciplinary perspectives. Thus, social scientists should conceptualize more integrative and relational models that simultaneously recognize the multiple contexts through which social and cultural inequities are produced in STEM majors and, presumably, a much wider variety of educational contexts that extend beyond these fields.

Policy Implications

In addition to the theoretical implications generated through the analysis, there are a number of potential implications for policy efforts aimed at social equity in STEM majors. First, an effective strategy to retain women in STEM majors may be to focus on programs and practices that foster social integration. In particular, programs aimed at creating and sustaining study groups for female STEM majors appears to significantly decrease the likelihood of these students leaving for other areas of study. Of course, the survey items tell us nothing about the qualities of study groups that make them effective (e.g., disciplinary affiliation, size), and contradictory findings in previous research (Gayles & Ampaw, 2014) suggest there are complex dynamics at work in these contexts. Thus, future work should utilize more context-specific designs to examine the exact features of study groups that impact rates of retention. In fact, it may turn out that study groups are simply incidental to increased retention, and that it is the social ties and associated dispositions developed through these groups that do the actual work. Thus, study groups may be one of many different social structures in which female students form the ties and dispositions that decrease rates of switching among those who would otherwise persist to graduation in a STEM major.

Another factor that appears important for the retention of female students in STEM majors is the need to work more than quarter-time (i.e., 11+ hours per week). Previous research has found that working at low-intensity levels (up to 20 hours per week) can actually increase rates of bachelor’s degree completion for all students, while high-intensity levels (more than 35 hours per week) decreases rates of completion (Roksa, 2011). Thus, future work should examine these impacts in the specific context of STEM majors and gender to determine the thresholds and types of work that both increase and decrease the likelihood of retention in these fields. This work can then be used to create targeted financial support and employment opportunities for female students that must work beyond low-intensity levels while pursuing a STEM major.

Finally, the results from our analysis suggest that sweeping scaled-up changes may not be a very productive way to change the social dynamics of switching patterns in STEM majors. At the very least, it appears to be important to consider each major as a unique social context; a figured world with its own meanings and rules of engagement and transformation (Holland, Lachicotte Jr., Skinner, & Cain, 1998). This is especially true in computer science fields where female students are most likely to leave the STEM fields altogether. Policymakers should also allow room for variations across IHEs. For instance, female students are more likely to switch out of STEM entirely while attending doctoral-granting institutions. In short, we argue that a more effective (and efficient) strategy may be to organize locally generated policy changes rather than opting for larger “silver-bullet” reform movements that often fail to understand the positional systems of meaning and action that constitute these complex social and cultural environments.

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Appendix

Appendix Table 1. **Descriptive Statistics for Beginning Postsecondary Students who Began their Postsecondary Education in a Bachelor's Program (N=5,200)**

Variables	All (N=5,200)		STEM (N=1,260) Non-Switcher (N=780)		STEM (N=1,260) Switcher (N=480)		Non-STEM (N=3,940) Non Switcher (N=2,290)		Non-STEM (N=3,940) Into STEM (N=260)		Non-STEM (N=3,940) Switcher (N=1,390)	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Theory of Social and Cultural Reproduction												
Demographic & Family Background												
Female	0.562	0.009	0.301	0.021	0.373	0.028	0.641	0.013	0.489	0.044	0.661	0.017
Race												
White	0.691	0.017	0.671	0.028	0.618	0.034	0.720	0.019	0.648	0.037	0.688	0.022
Black	0.105	0.013	0.079	0.017	0.156	0.025	0.099	0.011	0.074	0.027	0.117	0.019
Hispanic	0.098	0.007	0.093	0.022	0.128	0.023	0.088	0.009	0.099	0.022	0.105	0.012
Asian	0.058	0.005	0.112	0.016	0.053	0.012	0.046	0.006	0.098	0.019	0.041	0.007
Other	0.048	0.004	0.045	0.009	0.044	0.011	0.046	0.006	0.081	0.022	0.049	0.006
Parents' Education (BA or above)	0.573	0.009	0.657	0.021	0.550	0.032	0.570	0.014	0.618	0.037	0.534	0.018
Income*	68937.3	1155.2	72851.0	3070.9	66761.0	2952.7	69944.0	1614.3	68972.5	4461.0	66004.3	1746.8
College Preparedness												
Admission Test Score (ACT or SAT)	10.531	0.051	11.397	0.108	10.602	0.124	10.446	0.063	10.763	0.145	10.128	0.065
High School GPA (3.5~4.0, or A- or A)	0.495	0.011	0.626	0.024	0.482	0.030	0.484	0.015	0.573	0.042	0.431	0.018
Highest level of HS Math (Calculus)	0.280	0.007	0.524	0.025	0.302	0.024	0.235	0.011	0.407	0.036	0.185	0.012
Incoming College Credits	0.408	0.011	0.524	0.022	0.408	0.030	0.400	0.015	0.384	0.038	0.365	0.018
Social and Academic Integration												
Tinto's Theory of Student Departure												
Academic Integration												
College GPA, 2004	2.969	0.015	3.125	0.027	2.734	0.047	3.037	0.019	2.966	0.055	2.863	0.027
Percent of STEM credits in all credits earned in first year	28.5	0.5	56.8	1.0	39.3	1.4	19.9	0.5	39.1	1.9	21.0	0.6
Highest mathematics in first year												
No math	0.365	0.010	0.158	0.017	0.316	0.026	0.412	0.016	0.281	0.034	0.435	0.018
Precollege-level math	0.083	0.005	0.033	0.008	0.088	0.020	0.088	0.008	0.066	0.019	0.104	0.011
Introductory math	0.328	0.011	0.194	0.025	0.269	0.028	0.371	0.014	0.293	0.035	0.359	0.020
Calculus/advanced math	0.224	0.008	0.615	0.025	0.326	0.025	0.129	0.008	0.359	0.036	0.102	0.010
STEM GPA compared to non-STEM GPA in first year****	2.562	0.023	2.649	0.045	2.472	0.060	2.598	0.032	2.622	0.073	2.480	0.041

***Appendix Table 1*, continued. Descriptive Statistics for Beginning Postsecondary Students who Began their Postsecondary Education in a Bachelor's Program (N=5,200)**

Variables	All (N=5,200)		STEM (N=1,260) Non-Switcher (N=780)		STEM (N=1,260) Switcher (N=480)		Non-STEM (N=3,940) Non Switcher (N=2,290)		Non-STEM (N=3,940) Into STEM (N=260)		Non-STEM (N=3,940) Switcher (N=1,390)	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
*Social Integration***												
Large classes, 2004	0.374	0.011	0.434	0.022	0.375	0.025	0.345	0.013	0.470	0.044	0.369	0.018
Informal meeting with faculty, 2004	0.078	0.005	0.071	0.010	0.058	0.011	0.079	0.007	0.106	0.023	0.082	0.010
Talking to faculty outside of class, 2004	0.189	0.009	0.172	0.018	0.153	0.023	0.204	0.012	0.242	0.034	0.178	0.013
Meeting with academic advisor, 2004	0.229	0.008	0.213	0.017	0.170	0.018	0.239	0.011	0.277	0.034	0.233	0.013
Study groups, 2004	0.161	0.006	0.230	0.018	0.154	0.019	0.142	0.009	0.197	0.027	0.149	0.011
Clubs, 2004	0.172	0.007	0.193	0.016	0.156	0.020	0.173	0.009	0.170	0.027	0.165	0.013
Financial Context of Rational Choice												
Worked More than 10 hrs per week, 2004	0.410	0.011	0.314	0.021	0.453	0.030	0.419	0.015	0.361	0.040	0.443	0.015
Cumulative Federal Student Loan through 2006*	5812.1	131.6	5439.2	282.2	5027.5	307.2	6256.5	185.8	5250.6	448.2	5699.3	221.0
Pell grant: number of years received, 2006***	0.736	0.026	0.632	0.069	0.774	0.070	0.745	0.034	0.701	0.090	0.770	0.040
Expected family contribution, 2004*	13542.7	333.9	15062.5	968.1	13095.5	918.3	13852.3	481.1	13853.8	1326.6	12335.9	503.9
Receiving help repaying loans	0.061	0.004	0.043	0.010	0.054	0.013	0.071	0.006	0.044	0.014	0.059	0.008
Cost of attendance*	18306.0	243.4	19734.4	500.3	16845.6	504.0	18840.6	300.7	17546.4	636.2	17315.0	276.9
Institutional Characteristics												
HBCU & HIS	0.104	0.014	0.087	0.028	0.163	0.026	0.092	0.012	0.105	0.029	0.112	0.019
First Institution Selectivity (Very selective)	0.247	0.019	0.362	0.028	0.282	0.036	0.218	0.016	0.290	0.041	0.208	0.024
Doctoral-granting Institution	0.431	0.018	0.533	0.030	0.480	0.037	0.401	0.018	0.477	0.045	0.396	0.023

Note. See Appendix table 1 for detailed variables description. All means and standard errors are weighted for the study's sampling design. * Raw values were presented here, but those were transformed with a natural logarithm in the analysis. ** These variables were recoded to range from 0 (never or sometimes) to 1 (often). *** This variable ranged from 0 (No Pell grant) to 3 (3 years). **** This variable ranged from 1 (Considerably lower; lower than non-STEM GPA by at least one grade point) to 5 (Considerably higher; higher than non-STEM GPA by at least 1.0 grade point). Raw scales were presented here, but the last three categories were grouped as a reference in the analysis.

***Appendix Table 2*. Variable Descriptions**

Variables	Description
Theory of Social and Cultural Reproduction	
Demographic & Family Background	
Gender	Gender was measured as male (=0) and female (=1). Male is a reference group.
Race	Originally, race was measured as White, Black or African American, Hispanic or Latino, Asian, American Indian or Alaska Native, Native Hawaiian/other Pacific Islander, Other, and More than one race. However, because of the low proportion of some minority groups, eight racial categories merged into five categories; White, Black, Hispanic, Asian, and Other. White and other are a reference group and all others were included as dummy variables.
Parents' Education (BA or more)	Parents' education was measured as the highest level of education of either parent of the respondent during the 2003-04 academic year, and merged into Bachelor's degree (=1) or more and less than 4 years of college (=0).
Income	Income indicates the respondents' Adjusted Gross Income (AGI) in 2002. For independent students, this is the AGI for the parents and for independent students, this is the AGI for the respondent. This was transformed with a natural logarithm in the analysis after recoding 0 values into 50.
College Preparedness	
Admission Test Score (ACT or SAT)	Admission Test Score indicates the SAT I (verbal and math) combined score or the ACT composite score converted to an estimated SAT I, which scales from 400 to 1,600. In the analysis, this score was divided by 100.
High School GPA (3.5~4.0, A- or A)	High School GPA indicates the high school grade point average. This was converted into a dummy (3.5 ~ 4.0, A- to A = 1; 3.0 ~ 3.4, B to A- or less = 0).
Highest level of HS Math (Calculus)	Highest level of HS Math indicates the highest level of math the respondent completed among Algebra2, Trigonometry/Algebra II, Pre-calculus, and Calculus. This was converted into a dummy (Calculus = 1; others = 0).
Incoming College Credits	Incoming College Credits indicates college credits that the respondent earned while he/she was in high school. This was coded as a dummy (Yes = 1; No = 0).
Tinto's Theory of Student Departure	
Academic Integration	
College GPA, 2004	College GPA indicates the student cumulative Grade Point Average (GPA) in academic year 2003-2004, which scales from 0 to 400. In the analysis, this was divided by 100.
Percent of STEM credits in all credits earned in first year	This variable indicates the total number of STEM course credits divided by all course credits earned during the first year of enrollment. This was converted into three dummy variables in the analyses: Lower than 25 percent, 25-49 percent, and 50 percent or higher.
Highest mathematics in first year	This variable indicates the highest level of math courses in which a student earned one or more credits during the first year of enrollment. This consists of four categories: no math, precollege-level math only, introductory math (precollege-level math plus college-level math and college-level math/statistics only), and calculus or advanced math.
STEM GPA compared to non-STEM GPA in first year	This variable indicates the difference between STEM GPA and non-STEM GPA during the first year of enrollment. Five categories includes STEM GPA (1) lower than non-STEM GPA by at least one grade point (Considerably lower), (2) lower than non-STEM GPA by 0.5 to 1.0 grade point, (3) about the same as non-STEM GPA, (4) higher than non-STEM GPA by 0.5 to 1.0 grade point, and (5) higher than non-STEM GPA by at least 1.0 grade point (Considerably higher). The last three categories (3), (4), and (5) were converted into one reference group in the analyses.

***Appendix Table 2*, continued. Variable Descriptions**

Variables	Description
Social Integration	This variable was originally measured as 'never', 'sometimes', and 'often' and converted into a dummy (often = 1; never or sometimes = 0).
Large classes, 2004	Large classes indicates whether or how often respondent attended large lecture classes during the 2003-04 academic year.
Informal meeting with faculty, 2004	Informal meeting with faculty indicates whether or how often the respondent had informal or social contacts with faculty members outside of classrooms and the office during the 2003-04 academic year.
Talking to faculty outside of class, 2004	Talking to faculty outside of class indicates whether or how often the respondent talked with faculty about academic matters outside of class time (including email) during the 2003-04 academic year.
Meeting with academic advisor, 2004	Meeting with academic advisor indicates whether or how often the respondent met with an advisor concerning academic plans during the 2003-04 academic year.
Study groups, 2004	Study groups indicates whether or how often the respondent attended study groups outside of the classroom during the 2003-04 academic year.
Clubs, 2004	Clubs indicates whether or how often the respondent participated in school clubs during the 2003-04 academic year.
Financial Context of Rational Choice	
Worked More than 10 hours per week, 2004	Worked More than 10 hrs per week indicates whether the average hours the respondent worked per week exceeded 10 hours during the 2003-04 academic year (Yes = 1; No = 0).
Cumulative Federal Student Loan through 2006	Cumulative Federal Student Loan through 2006 indicates the cumulative Stafford and Perkins loan amount the respondent borrowed through 2006. This was transformed with a natural logarithm in the analysis after recoding 0 values into 50.
Pell grant: number of years received, 2006	Pell grant indicates the number of years the respondent received a Pell grant through 2006. This was converted into two dummies in the analysis (1~2 years and 3 years). No Pell grant is a reference group.
Expected family contribution, 2004	Expected family contribution indicates the composite estimate of the federal Expected Family Contribution used in need analysis, using the 2003-04 Pell grant record and the 2003-04 CPS record. This was transformed with a natural logarithm in the analysis after recoding 0 values into 0.5.
Receiving help repaying loans	Receiving help repaying loans indicates whether anyone, such as a family member or friend, helped the respondent to repay his/her undergraduate loans as of January 1, 2009 (Yes = 1; No = 0). The respondent who skipped this question was recoded to 0.
Cost of attendance	Cost of attendance indicates the price of attendance or total student budget. This was transformed with a natural logarithm in the analysis.
Institutional Characteristics	
HBCU & HIS	HBCU & HIS indicates whether the first institution the respondent attended during the 2003-04 academic year is designated either as a Historical Black College (or University) or a Hispanic Serving Institution (Yes = 1; No = 0).
First Institution Selectivity (Very selective)	First Institution Selectivity indicates the level of selectivity of the first institution the respondent attended during 2003-04 academic year. This was converted into a dummy (Very selective = 1; Others =0).
Doctoral-granting Institution	Doctoral-granting Institution indicates the Basic Carnegie classification of the first institution the respondent attended. This was converted into a dummy (research and doctoral institutions = 1; others = 0).

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The authors would like to thank the following people who contributed critical feedback: Mark Connolly, Elaine Seymour, Heather Thiry, and Erika Vivyan. In addition, we would like to thank Sarah Bell for her assistance with the figures and Kurt Brown for his editorial work. The analysis conducted in this paper was supported by grants awarded from the National Science Foundation (DUE-1224550) and Alfred P. Sloan Foundation (2012627). Any opinions, findings, or conclusions expressed in this paper are those of the authors and do not necessarily reflect the views of the National Science Foundation, the Alfred P. Sloan Foundation, WCER, or cooperating institutions.