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Major Movement: Examining Meta-Major Switching at Community Colleges

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Abstract

Evidence of inefficient course-taking patterns at community colleges has spurred policy conversations about how to ensure effective course sequences. Structural reforms, like guided pathways, seek to reduce major switching as a means to streamline student course taking and eliminate unnecessary credits. By placing students into broad fields of study—called meta-majors—and encouraging persistence within that general field (where coursework narrows toward a specific program over time), community colleges may help students progress toward their desired degree. But how often do students leave that meta-major, and what predicts meta-major switching? We use national data to examine meta-major switching at community colleges. Our findings suggest that almost 40 percent of students switch between meta-majors (eight broad major fields, plus undecided) between their first and third years of college. We describe the varied destinations and predictors across origin meta-majors and consider implications for colleges as they seek to assess ongoing reforms.

Keywords

community college; major choice; major switching; guided pathways; meta-major; regression

Community colleges serve as an on-ramp to postsecondary education for many Americans, but the open-access mission at community colleges is typically paired with cafeteria-style course offerings (Bailey et al., 2015). Many students take courses early in their college experience that do not contribute to their desired credential; evidence of inefficient course-taking patterns bolstered support for reforms to ensure effective course sequences (Bailey et al., 2015; Fink et al., 2018; Jenkins & Cho, 2012). Major choice is a longitudinal process with important implications for community college students' course sequences and college outcomes. Major switching[1]—where students leave their initial major for a different major—may slow students' progress toward their degree (Jenkins & Cho, 2012).

[6]Kline, R. B. (2016). Principles and practice of structural equation modeling (4th ed.). New York, NY: The Guilford Press.

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Concerns over major nonpersistence at community colleges motivated recent structural proposals to streamline curricular pathways using meta-majors, one component of the sweeping guided pathways reforms (Bailey et al., 2015; Jenkins, 2014; Jenkins & Cho, 2012). Meta-majors are broad fields comprising majors that, ideally, share early lower-division coursework (Bailey et al., 2015). Meta-majors are designed to guide students through early academic requirements before they settle on a specific program (Waugh, 2016), but there is little underlying evidence about community college students' major selection and major switching (both within or between meta-majors). As colleges across the country attempt wholescale restructuring to enact guided pathways, they need information about how students make course choices and, in contexts with limited resources, which students to target for additional supports. This study illustrates patterns of switching between broad major fields in order to offer insights for colleges as they implement meta-majors and other reform components aimed at improving the effectiveness of course sequences and helping students meet their educational goals.

Student Pathways Through Community Colleges

Community colleges democratize access to higher education but are criticized for having low rates of student success. Sixty percent of community college entrants fail to earn any credential within six years of entrance, with only 16% of noncompleters still enrolled in college (Chen et al., 2019). Researchers contend that students' low rates of entering a program of study within the first year and high rates of major switching contribute to low rates of degree attainment (Bailey et al., 2015; Jenkins & Cho, 2012).

Researchers who support the "structural hypothesis" portend that community college students are more likely to persist and succeed in programs that are tightly and consciously structured, through both institutional policies and procedures but also through "norms and nudges" that inform students' decisions (Scott-Clayton, 2011, p. 2). The current pathway through community college resembles a "shapeless river," and the lack of structure contributes to extended, meandering pathways for students (Scott-Clayton, 2011). Structural critics argue that community colleges should offer more institutional structure and guidance for students as they navigate college (Rosenbaum et al., 2007).

Concerns over structure and inefficient pathways through college were the crux of the arguments laid out in Bailey et al.'s (2015) *Redesigning America's Community Colleges*. The authors described most community colleges as enacting a *cafeteria model*, where students pick courses based on whims or scheduling rather than following structured sequences to reach their educational and career goals. Bailey et al. proposed an alternative approach, *guided pathways*, where students would enroll in streamlined course sequences. The proposed course sequences would start with general coursework applicable to several majors within a broad field, referred to as a meta-major, before taking specialized coursework for a specific major. Under guided pathways, career counseling would be provided early in college to ensure students select a meta-major that is aligned with their

[1]We use the terms "major switching" and "major nonpersistence" interchangeably throughout this article.

desired career; structured advising throughout the pathway would keep students on track to their goal.

Attention to student pathways through community college has grown in response to public scrutiny over college affordability and returns, combined with increased pressure within states to rapidly improve degree attainment (Schudde & Grodsky, 2018). Policymakers in many states turned to guided pathways initiatives to address inefficient course taking and low rates of degree attainment (e.g., California, Florida, Washington, and Texas have adopted guided pathways in some form.); more than 200 community colleges engaged in some guided pathway reforms by spring 2017 (Jenkins et al., 2017). These concerns are nothing new—for decades, research illuminated credit loss in transfer, inefficient pathways, and difficulties selecting courses and majors (e.g., Brint & Karabel, 1989; Cohen & Brawer, 1989; Cohen et al., 2013; Dougherty, 1994; Grubb, 1991; Rosenbaum et al., 2007). However, the emphasis on developing structured pathways has recently become a powerful reform movement in higher education.

Illuminating Major Choice and Switching at Community Colleges

Despite the attention to guided pathways, which many colleges enact through several reforms, including creating meta-majors and increasing student supports, the literature on how students select and move between majors at community colleges is sparse. A few pertinent studies examine major choice at community colleges, but none focus on major switching. In this section, we describe the extant literature on community college major choice and its implications, including a discussion of the motivations for illuminating major switching patterns.

Major Choice

Most extant research on major choice at community colleges, as in the four-year sector, focused predominantly on the science, technology, engineering, and math (STEM)/ non-STEM dichotomy. The literature highlights existing inequities in student subgroup representation in STEM fields (Hardy & Katsinas, 2010; Nora & Rendón, 1990; Sanders & Lubetkin, 1989) and explores the experiences of students in STEM majors at community colleges (Hester, 2011; Lester, 2010), including studies focused on transferring to baccalaureate-granting institutions in STEM fields (e.g., Dowd, 2012; Packard et al., 2011; Packard & Jeffers, 2013; Wickersham & Wang, 2016).

A smaller subset of research examined initial major choice at community colleges (Baker, 2018; Wang, 2013). Wang (2013) used national data to examine predictors of selecting STEM majors, illustrating that the predictors (e.g., self-efficacy, academic integration, participation in developmental coursework) of STEM choice differ across two- and four-year students. For example, measures of prior exposure to math and science courses strongly predicted STEM interest among four-year college entrants but were less influential (though still positive) for community college students. Baker (2018) examined which majors students included in their “consideration sets” for initial major. To date, Baker is one of the few scholars to study meta-majors, outside of implementation studies, and consider assumptions of the reforms. She argued that meta-majors would be most useful to students if they clustered majors in consistent groups and if the majors in those consideration sets aligned with the meta-majors used at their community college. Her results suggest some demographic variation in how students build their consideration sets. For example, Asian, Latino, and older students were more likely to consider stable clusters of majors (often including similar sets of majors in their consideration sets) than were other student subgroups.

Major Switching

Despite growing concerns over inefficient pathways through community college, very little research has been conducted on nonpersistence in majors among community college students. A 2013 report from the National Center for Education Statistics (NCES) found a high degree of major switching among students at associate degree–granting institutions (the analyses included both private and public two-year institutions), with 33% leaving STEM majors, 31% leaving education, 29% leaving humanities, 26% leaving business, and 20% leaving health sciences (Chen & Soldner, 2013). Chen and Soldner (2013) examined predictors of leaving STEM majors using the 2004/2009 Beginning Postsecondary Students Longitudinal Study (BPS:04/09) and found that both overall GPA and grades in STEM coursework predicted remaining in a STEM major. However, these authors did not explore major switches beyond STEM to non-STEM.

Not all major switching is necessarily problematic. Switching to a higher-return major might improve labor market outcomes for students later on, given evidence of variation in returns across sub-baccalaureate degrees (Bahr, 2019; Xu & Trimble, 2016), though students may be unaware of returns for certain majors (Baker et al., 2018). Research also suggests that switching from undeclared status into a major improves student progress toward a credential. Compared with peers whom entered a major early in college, students who are undeclared in their first year are less likely to accrue at least 60 credits and less likely, among those who persist, to enroll in coursework that counts toward their final degree (Jenkins & Cho, 2012; Monaghan & Attewell, 2015). Students who enter community college undeclared are at greater risk of accumulating unnecessary lower-division credits that do not contribute toward a degree (Fink et al., 2018).

The extant evidence on community college majors largely relies on major groupings, used by researchers to distinguish between similar and distinct majors, to understand major choice and major switching. With the exception of Baker (2018) and the implementation studies of the guided pathways reforms (e.g., Jenkins et al., 2017), the literature has not focused on meta-majors, which are a tool used in higher education practice to improve student success. Here, we seek to create baseline knowledge about how community college students move between meta-majors. However, we rely on the extant literature using major groupings to operationalize and examine major choice and switching because national data does not capture meta-majors specific to each college context.

Predictors of Meta-Major Switching in Community Colleges: Building a Conceptual Framework

To date, little evidence has been offered about existing patterns of major switching at community colleges or about predictors of how students will move between majors. To guide our inquiry into meta-major switching among community college entrants, we reviewed extant research on student success at community colleges and major switching at four-year institutions. Most research on major switching focuses on students at four-year colleges and primarily examines nonpersistence in STEM majors (e.g., Astorne-Figari & Speer, 2019; Crisp et al., 2009; Ferrare & Lee, 2014; George-Jackson, 2011; Griffith, 2010; Ost, 2010; Price, 2010; Riegle-Crumb et al., 2016), but it is important to acknowledge that student characteristics and enrollment patterns tend to differ across two- and four-year colleges (Schudde & Brown, 2019). Research on community college student outcomes focuses primarily on persistence and completion (e.g., Braxton et al., 2014; Calcagno et al., 2008; Roksa, 2006) rather than on persistence within a field of study. Basing our work on our review of prior literature, we identified three main constructs that may inform meta-major switching among community college entrants: student background, including demographics; college experiences, including early college academic and social integration and performance; and institutional characteristics, including proxies for institutional resources.

Student Background

Most of the literature on college persistence, in both two- and four-year institutions, explores the contribution of pre-entry characteristics such as gender, race, and socioeconomic status, along with educational background measures (e.g., Adelman, 1999; Braxton et al., 2014; St. John et al., 1996). Many of these measures have also been shown to play a role in initial major choice, with some evidence that demographic measures predict major switching as well. At both two- and four-year colleges, women tend to gravitate toward fields such as education, nursing, and the social sciences for their initial major choice, whereas men are overrepresented in fields such as business, mathematics, the natural sciences, and engineering (Ma, 2009; Morgan et al., 2013). In Baker's (2018) exploration of initial major consideration sets, men exhibited more closely related majors in their consideration sets, which may suggest that they are more likely to stay within meta-majors if they switch.

The relationships between demographic background and major nonpersistence at community colleges are unclear. Research on STEM majors in the four-year context suggests that women and students of color are more likely to leave those majors (e.g., Astorne-Figari & Speer, 2019; Crisp et al., 2009; Ferrare & Lee, 2014; George-Jackson, 2011; Griffith, 2010; Ost, 2010; Price, 2010; Rask, 2010), though Griffith (2010) found that differences in academic preparation and educational experiences explained much of the variation in major persistence.

Socioeconomic status (SES) has also been linked to initial major choice (Leppel et al., 2001; Ma, 2009) and to lower rates of college persistence and completion (Bailey et al., 2005; Dougherty & Kienzl, 2006). Breen and Goldthorpe (1997) proposed that college students from low-SES backgrounds may be more averse to risk and may perceive some majors as leading to uncertain job prospects. Findings from four-year institutions suggest that students from lower socioeconomic backgrounds are more likely to initially choose majors with higher returns—including engineering and business—than their more affluent peers (Davies & Guppy, 1997; Ma, 2009). It is plausible that SES predicts not only initial major choice but also major switching (in particular, which majors students switch to, among those who switch), given that research also indicates that lower-SES students may be more likely to avoid majors they perceive as having fewer payoffs in the labor market (Monaghan & Jang, 2017).

Experiences During College

The extant literature on major switching at four-year colleges emphasizes academic performance and other academic experiences early in college as predictors of major nonpersistence, at least in the oft-studied STEM fields. This is not surprising given the array of research that linked academic achievement and ability measures to major choice (e.g., Arcidiacono et al., 2010; Ma, 2009; Stinebrickner & Stinebrickner, 2011; Wang, 2013). Ost (2010) examined persistence in life and physical science majors at a large, elite research university and found a significant impact of college grades on major persistence but little evidence that high school preparation directly influenced major persistence. Astrone-Figari and Speer (2019) demonstrated that earning lower grades within a major field increases the probability that students switch to majors that are very different from the ones they leave.

Course-taking patterns and alignment of coursework with major intentions are also probable predictors of major persistence. Intensity of STEM course-taking, type of math courses taken, and success in STEM courses predict persistence in STEM majors among students at both associate and bachelor's degree–granting institutions (Chen & Soldner, 2013; in four-year context: Griffith, 2010; Price, 2010). In the community college context, participation in developmental education (dev-ed) courses may also influence major choice and switching. Students placed into remediation are not always aware that their developmental coursework does not count toward a degree and may be discouraged once they find out (Deil-Amen & Rosenbaum, 2002; Jaggars & Hodara, 2011). Dev-ed reformers note that the slow pace of developmental sequences, particularly in mathematics, may function as a hurdle to students interested in a math-intensive major (Bryk & Treisman, 2010).

Other impediments to progress toward a community college degree, such as inconsistent enrollment and attending college on a part-time basis, may predict attrition from some majors. Enrollment patterns, including stopping out (breaks in college followed by re-enrollment) or attending part-time, have been linked to lower persistence (Fike & Fike, 2008; Park, 2012). Although research has not examined the relationship between enrollment patterns and major switching, community-college reformers emphasize the importance of consistent full-time enrollment in making timely progress toward a degree (Bailey et al., 2015).

Several theories tout the role of campus life in predicting student development and success: Astin's (1993) involvement, Tinto's (1993) integration, and Kuh's (2001) student engagement.[2] Research on community college students suggests that classroom interactions influence community college students' subsequent outcomes, such as persistence, transfer, and degree attainment (Barnett, 2011; Deil-Amen, 2011; Schudde, 2019). Wang's (2013) research on STEM major selection suggested that academic engagement negatively predicted initially selecting a STEM major among community college students, though it is unclear how academic engagement predicts subsequent major switching. Faculty perceptions, including their expectations for how students learn and the knowledge they bring to the classroom, may play a role in major persistence (Daempfle, 2003). Likewise, positive interactions with peers, particularly interactions that support academic integration into the major, may improve major persistence. Findings from the four-year sector seem to support this hypothesis; Ferrare and Lee (2014) found that participation in study groups increased persistence in STEM majors.

Institutional Characteristics

Research on the institutional factors associated with major persistence focused primarily on STEM persistence at four-year institutions, often emphasizing the roles institutional selectivity and average peer test scores play in STEM major persistence (e.g., Chang et al., 2008, 2014; Espinosa, 2011). Given that community colleges tend to be open-access institutions, it seems plausible that STEM majors may be more inclusive than the same majors at more elite institutions. At the same time, community colleges struggle with resources (Schudde & Grodsky, 2018), and institutional resources and support services may be vital to success.

General institutional characteristics, such as enrollment size, may predict institutional capacity for certain majors. Institutional factors like cost (average net student tuition) and proxies for institutional resources (e.g., faculty:student ratio, faculty salaries) appear to influence college outcomes and are often included in models that predict college outcomes and beyond (e.g., Bound et al., 2010; Pascarella et al., 1992; St. John et al., 1996). Measures of institutional resources, such as the availability of career and advising services, may be a useful proxy for support services.

Evidence suggests that student and faculty diversity are also important in predicting retention in STEM majors, at least in the four-year context (Griffith, 2010; Price, 2010). In lieu of major-specific measures obtained from each institution (as is more feasible with a small sample of colleges), institutional composition measures can partially get at this issue. Bailey et al. (2005) argued that including institutional compositional variables (i.e., percentage of Pell recipients) captures the indirect or peer effects of that characteristic if the analysis concurrently controls for the same individual characteristics.

Summary

Overall, our conceptual framework presumes that the combination of demographic background, educational experiences, and college characteristics predicts individuals' major switching behavior. We examine patterns of meta-major switching and the predictors of

[2]The models emerged based on research in the four-year college setting. Although each theorizes how engaging in college life impacts student development, each has its own nuances and aims. See Wolf-Wendel et al. (2009) for a thorough review.

movement between meta-majors, using measures informed by our review of the literature. We anticipate that the determinants of meta-major switching may not be the same across different fields; therefore, we explore the predictors separately across meta-majors. Though there is probably variation within meta-majors (as illustrated in the literature on STEM major departure: e.g., Kokkelenberg & Sinha, 2010; Ost, 2010; Rask, 2010), we focused on switching between meta-majors to engage with the ongoing reforms within the community college sector.

Research Questions

We ask several interrelated research questions (RQs):

1. Which students select different meta-majors during the first year of college? How does the makeup of students in those meta-majors change by the third year?
2. What proportion of community college students switch between meta-majors within their first three years of study? When students switch meta-majors, what type of major do they switch to?
3. What are the predictors of switching meta-majors? How do the predictors vary based on students' origin major?

Methods

We used NCES's 2012/17 Beginning Postsecondary Students Longitudinal Study (BPS:12/17), paired with descriptive statistics and regression analyses, to answer our research questions. Next, we describe the data and the sample, followed by our analytic approach.

Data Sources

The BPS:12/17 is a nationally representative survey that follows a cohort of first-time, beginning postsecondary students. We focused on the first two waves of data[3] to study patterns of meta-major switching that occurred within the first three years since initial college entrance. The BPS:12/17 collected data on students who first enrolled in a postsecondary institution in the 2011–2012 academic year, including information on their background, educational plans and progress, and college experiences; the first follow-up in spring 2014 continued tracking their experiences and outcomes. The rich nature of the data makes it ideal for examining processes that influence student decisions during college.

The BPS:12/17 data include responses from 22,532 students who participated in the study. We restricted our sample to students who started at a public two-year institution ($N = 6,510$) and who had not transferred to another institution by 2014 ($N = 5,030$).[4] Because major offerings may differ across institutions, we decided to focus on students with enrollment at the same public two-year institution. We also dropped 780 participants who did not answer

[3]Although we used the data from 2011–12 and 2014 in our study, we relied on updated measures of majors and enrollment—released with the final 2017 update—for the baseline and 2014 follow-up, as advised by staff at NCES.
[4]All sample sizes were rounded to the nearest ten, in accordance with statistical standards for restricted-use data from the National Center for Education Statistics.

the major survey item in either the first or the second wave. The resulting analytic sample included 4,250 community college students. When we apply the BPS analysis weight (WTA000) to account for subsampling, unknown student eligibility, and nonresponse, our analytic sample represents 973,636 in the population of community college entrants who did not transfer to another institution within the first three years and provided information about their major. Of the 4,250 students, 820 had earned a degree or certificate by June 2014 and were no longer enrolled, 1,570 were still enrolled and had not earned a degree, and 1,860 were not enrolled and had not earned a degree.

We provide a complete list of analytic variables in Table 1, which includes variable descriptions and summary statistics for the entire analytic sample; 55.7% of the analytic sample identified as female. Approximately 53.5% identified as White, 25.3% as Hispanic, 12.3% as Black, 4.6% as Asian, and 4.4% as another racial group. The average age at initial enrollment was 21.6, with a standard deviation of 7.5, which indicates a fairly wide range of age compared with a more traditional college-going population we might see attending four-year colleges. Among students in our sample, 9% were married, and 13% had at least one dependent child. More than two-thirds were financially dependent on their parents. The average student in the analytic sample came from a family with a household income of $46,390 (note that we used logged family income in the analysis). Seventy percent of students came from families where neither parent had earned at least a bachelor's degree. Fewer than half of students were enrolled full-time. About half of the sample used academic advising services, and 23.6% and 10.3% of the sample used academic services and career services, respectively, during their college entry year. In addition, 17.3% of students stopped out, having taken at least one term (not including summer) off from schooling by the 2014 follow-up. At the average college attended by students in the sample, 46.9% of attendees identified as non-White, and 40.3% received a Pell Grant.

Measuring Meta-Majors and Meta-Major Switching

We developed meta-majors following examples from meta-majors used in states implementing guided pathways–style reforms (Baker, 2018; Jenkins et al., 2017). Across the 10 states[5] for which we found specific information about the meta-majors they were using, colleges varied in the total number of meta-majors they offered, ranging from five to nine in total, with a mode of nine. There was some variation across states/colleges in the names of the meta-majors and how sizable broad fields of study were divided into component meta-majors. The nine types of meta-majors included STEM; arts, humanities, communications, and design (with some states/colleges breaking these into more than one meta-major); business; education; health sciences (with some states/systems building a broad meta-major, while others had nursing/public health and allied/respiratory/occupational health as separate meta-majors); industry, manufacturing, and construction (with some systems offering an applied industry/technology meta-major); public safety; social and behavioral sciences and human services (with some slight variation in naming); and agriculture, nutrition, and culinary arts (in California and some colleges in Oregon only).

[5]Not all 10 states used statewide meta-majors, but we captured participating institutions within the state as of 2018 as documented by the Pathways Collaborative (2017) and gathered additional information from individual state/college websites as necessary. The 10 states included: CA, FL, GA, IN, MA, MS, OR, TN, TX, WA.

We used the meta-majors that were common across implementing states/colleges (e.g., we did not keep agriculture, since it was only used in two states, instead grouping it with industry, manufacturing, and construction). Our final meta-majors included STEM, humanities/ liberal, arts, social sciences, education, business, health sciences, industry/ manufacturing/agriculture/construction (IMAC), and public safety.

Because we used national data from colleges across varying contexts, our construction of meta-majors has some overlap conceptually with prior research that constructed major groupings in order to examine major choice and major switching. We acknowledge that this is imperfect, but see our inquiry as a jumping off point from which other studies can more explicitly study meta-major switching in specific contexts using the meta-majors and definitions from those contexts.

In the BPS, students were asked about their latest major during their first (BPS2012 measure “majors23”) and third year of the study (BPS2014 measure: “maj14”), where they were provided 23 response options, each of which has a broad classification of instructional programs (CIP) code (a two-digit identifier). The BPS did not offer students the option to report more than one major at a time. We used the CIP codes from students’ self-reported majors to place them into the meta-majors; alignment between CIP and meta-major was fairly straightforward, but in some cases, we drew on prior literature that performed major groupings, such as Leppel et al. (2001) and Zafar (2013), to place CIP codes within a meta-major. Appendix Table A2 describes the majors that comprise the meta-majors.

Almost five percent of community college entrants were undecided in their first year (2011), with 16.2% undecided by their third year (2014). For that reason, we included “undecided” as one of the meta-major categories, even though recent literature and reforms in community colleges are pushing for students to be on a major pathway early on and throughout their community college experience. If students provided a different meta-major in year 1 compared with year 3, we coded them as switching meta-majors. We found that 39.7% of community college entrants switched between the nine meta-majors (eight meta-majors plus undecided) at some point between their first and third years (see Table 1).

Missing Data

Survey research often suffers from high amounts of missing data, which can result from skipped responses or some other mechanism. In our analytic data, the proportion of missing values ranged from 0% to 7.6%. The primary missing values included 321 participants (7.6%) who failed to provide their first-year college GPA and 209 participants (4.9%) who replied “don’t know” regarding their parents’ highest education level. To preserve sample size, we used multiple imputation (MI) to impute the missing observations for first-year GPA and highest parental education. Multiple imputation entails averaging the outcomes across multiple imputed data sets and relies on the assumption that the data are missing at random, meaning that non-response probabilities do not depend on unobserved information (Rubin, 2005). Although the assumption is strong, MI is considered the most suitable choice for addressing missing data by many statisticians and applied researchers (Manly & Wells, 2015). We performed MI and created several completed copies of the dataset (in this case 20 copies), in which missing observations are replaced by plausible values instead of assuming one “true” response model (Royston & White, 2011). The imputation model included other covariates and the two major variables in addition to the BPS analysis weight (WTA000) and survey structure variables (i.e., PSU & Strata) to ensure the sample statistics were representative of all students who entered a two-year institution during the 2011–2012 academic year.

Analytic Approach

To address our research questions, we first leveraged descriptive statistics to highlight patterns of meta-major switching in the first three years of college among community college entrants. To address RQ 1, we described the characteristics of students in each of the meta-majors—STEM, humanities/ liberal arts, social sciences, education, business, health sciences, industry/ manufacturing/agriculture/construction (IMAC), and public safety—or undeclared status. To address RQ 2, we examined patterns of switching between meta-majors.

To understand the factors that predict switching (RQ 3), we used logistic regression. Our dependent measure captures whether a student switched between meta-majors within three years of initial entrance. Guided by our review of the literature, we included a host of different control measures, including background measures like race, gender, proxies for socioeconomic status; measures of student experiences during college such as their academic performance, involvement on campus (captured by a factor comprised of measures more in line with Astin’s (1993) “involvement”—which includes psychosocial investments in the college experience—than other conceptions of campus integration or engagement), enrollment patterns, and institutional characteristics.

Logistic regression modeling allowed us to predict the probability that a student will switch meta-majors within the first three years of community college. We used the following model:

$$Logit\ (p) = b_0 + b_1X_1 + b_2X_2 + \ldots. + b_kX_k \tag{1}$$

where p is the probability of switching meta-majors within three years, b_0 is the intercept, $X_1 - X_k$ are the independent variables, and $b_1 - b_k$ are the associated regression weights. The independent variables capture three domains that align with our conceptual framework: background characteristics, experiences during college, and institutional characteristics (see Table 1). The logit transformation ensures that the predicted probability of switching lies within the $0 - 1$ bound. This allows for a more realistic representation of the curvilinear association because of the dichotomous outcome variable, and it tends to linearize the association between the predicted outcome and the set of predictors (Raudenbush & Bryk, 2002).

We performed the logistic regression on the full analytic sample first, followed by additional logistic regressions on students who started in each meta-major, in order to examine predictors of switching overall and within origin meta-majors. To assess whether our model appeared sensitive to the type of student included in the analysis, we also performed some additional analyses on student subsamples based on their educational expectations and attainment and enrollment status. Overall, the results largely showed similar patterns across groups of students and did not lead us to make additional changes to the model.

Limitations

Because we relied on regression, the results we present do not represent causal relationships but rather correlations. However, given our interest in examining variation in switching patterns and predictors across a variety of meta-majors, using descriptive statistics and regressions with rich covariates is an appropriate strategy for addressing our research questions. To minimize bias, we included controls for demographic background, experiences during college, and institutional characteristics, but it is feasible that omitted variables may explain at least some of the observed patterns. For example, some measures identified in the literature on major choice—such as precollege measures like high school coursework and intrinsic/noncognitive measures, including self-efficacy, motivation, interest, and confidence (Crisp et al., 2009; Daempfle, 2003; Wang, 2013), or type of credits earned in the first year (Chen & Soldner, 2013)—were unavailable in the data. That said, the dearth of literature on major switching and sorting into and between meta-majors at community colleges means that our model, despite having potential limitations, makes a strong contribution to the literature and can serve as a base on which future research can be built.

Results

Descriptive Statistics: Examining Patterns in Major Choice and Major-Switching

In Table 2, we present the descriptive statistics for students in each initial meta-major (note that we present the distribution across meta-majors in the online Appendix; see Table A3). Humanities/liberal arts was the most popular meta-major (24%), followed by health sciences (19.4%) and STEM (13.9%). As illustrated in Table 2, there appears to be variation in the demographic make-up of initial meta-majors. Women account for 71, 76, and 85 percent of social science, education and health science meta-majors, whereas men account for 65, 76, and 86 percent of public safety, STEM, and IMAC meta-majors, respectively. The breakdown by race within meta-majors suggests that white students are somewhat overrepresented within undeclared, humanities/liberal arts, and IMAC compared with their overall proportion in the population. Black students appear somewhat overrepresented in health sciences or business and considerably underrepresented in undeclared, whereas Hispanic students appear overrepresented in education and public safety and somewhat underrepresented in STEM and IMAC. Students from the top family income quartile appear overrepresented in humanities/liberal arts and underrepresented in education and health sciences; students from the lowest income quartile appear overrepresented, compared with their percentage of the population, in health sciences and public safety. Among students undeclared in the first year, students from the lowest income quartile appear considerably underrepresented (only 12%) whereas those from the third income quartile appear substantially overrepresented (38%). Table A3 offers a clearer look at the distribution of students within specific demographic groups across meta-majors.

Table 3 presents an overview of student characteristics within third-year meta-majors, provided as percentages of students in various categories, with the difference of representation within those categories between first- and third-year major choices provided in parentheses in each row. The percentage of students who were undeclared in their third year (16.2%) was 3.5 times larger than in the first year (4.6%). This was followed by humanities/liberal arts (15.8%) and health sciences (15.2%). When we examine meta-major composition related to meta-major switching, there are some interesting changes in student characteristics. For example, women comprise the majority of undeclared students in 2014, increasing their representation by 15 percentage points since the first year. It also appears that the gender gap in STEM and business closed slightly, as women comprise a larger percentage of those meta-majors than in the first year (though they still are starkly underrepresented in STEM, making up only 29% of STEM meta-majors). As the number of undeclared students increased, the racial make-up of undeclared shifted, where White and Asian students are no longer overrepresented and Black students are approximately even with their representation in the population. The increase in the IMAC meta-major appears to be driven by non–first-generation college students, who were underrepresented in the meta-major during the first year but now appear overrepresented compared with their proportion in the population. The representation of students from the third income quartile in undeclared status dramatically decreased—by almost 12 percentage points—by 2014. The representation of those from the lowest income quartile increased by 10 percentage points, suggesting that students from the lowest income quartiles were more likely to switch from a meta-major into undeclared status over time. We also present the distribution *across* meta-majors in the online Appendix (see Table A4), which allows us to briefly examine how students with certain characteristics move between meta-majors over time.

More alarming than basic shifts in demographics are the overall patterns of meta-major switching. In Table 4, we present the distribution of meta-major switching between the first and third years (note that the cells outlined in bold highlight the students who did not switch between meta-majors). Although we know almost 40 percent of students switched meta-majors at least once, there was variation across origin meta-major. Anywhere from one-fourth to about half of students switched meta-majors, depending on initial meta-major. A particularly concerning result is the number of undeclared students who did not switch out—this would be the top major field where we would hope to see students leave. Of the students who were initially undeclared, 59.6% were still undeclared three years later. Among those who switched, the highest destination meta-majors were STEM (15.9%), followed by social sciences (5.2%). Just over half of those initially enrolled in humanities/ liberal arts meta-majors were still enrolled in that field in their third year; the top destination of those who switched was undeclared (which is not an improvement over general studies), followed by social sciences (7.2%), and STEM (6.7%). Students initially enrolled in public safety and IMAC were least likely to switch (followed closely by public safety), with about 71 and 77 percent, respectively, indicating it as their major three years later. For other meta-majors, more than one-third of students (or significantly more) originally entered under a completely different meta-major.

Predictors of Major Switching

Table 5 presents the results for a series of logistic regression models predicting switching between meta-majors. The first column captures regression results from the full sample and estimates switching between meta-majors overall. The subsequent columns include regression results from subsamples of community college students who initially enrolled in each of the eight meta-majors, where we fitted a separate regression model for each subsample to understand the predictors of switching out of that meta-major. For ease of interpretability, we present average marginal effects (AMEs) rather than log-odds or odds ratios, which we obtained using the margins command in Stata (Williams, 2012; Cameron & Trivedi, 2010). The AME represents the change in the predicted probability of the outcome for each one-unit change in a given independent variable, holding other independent variables at their mean.

Looking at predictors of meta-major switching overall (restricting the sample to examine students within specific initial meta-majors), we note several patterns. Women appeared more likely to switch meta-majors than men. Identifying as a woman was associated with a seven-percentage-point increase in the probability of switching meta-majors compared with identifying as a man ($AME = .070$, $SE = .022$, $p = .002$). Likewise, Hispanic students were more likely than White students to switch between meta-majors. Age was negatively associated with meta-major switching. For every two-year increase in age, there was a corresponding one-percentage-point drop in the probability of switching meta-majors ($AME = -.006$, $SE = .002$, $p = .014$).

In addition to student characteristics, college experiences appear to predict major switching. Students who received academic advising were almost six percentage points less likely to switch meta-majors than were students who did not ($AME = -.055$, $SE = .023$, $p = .018$). Stopping out—taking a break from college enrollment—was associated with a 17-percentage-point increase in the probability of switching meta-majors compared with continuous enrollment ($AME = .168$, $SE = .031$, $p < .001$). Finally, for each month enrolled, a student's predicted probability of switching meta-majors increased by one percentage point ($AME = .010$, $SE = .001$, $p < .001$).

When we turn to regressions estimated for students in each initial meta-major, some additional patterns emerge, particularly across race and gender. First, we see that identifying as a woman increases the probability of leaving STEM, where women appear underrepresented, and humanities/liberal arts, even after controlling for other background measures. For example, identifying as a woman, compared with identifying as a man, is associated with an 17-percentage-point increase the probability of switching out of the STEM meta-major ($AME = .165$, $SE = .066$, $p = .012$). We also observed some variation in leaving particular meta-majors by race. Identifying as Hispanic, compared with identifying as White, predicted leaving social sciences and business, whereas identifying Asian, compared with identifying as White, predicted staying in public safety. Parents' educational level predicted the switching out of particular meta-majors. Compared with students whose highest parental education was high school, additional levels of parental education positively predicted switching out of the social sciences, business, and public safety meta-majors. It looks like additional parental education negatively predicts switching out of the education meta-major, though the pattern is a little less clear (appears largely driven by students with parents who hold a doctoral degree). In addition, we see that higher educational expectations, compared with expecting a certificate/diploma, predicted switching out of some meta-majors, such as social sciences and IMAC (whereas educational expectations were not associated with meta-major switching overall).

Measures of college experiences (to the extent our model could capture them) appear to explain much of the switching out of particular meta-majors. Participation in dev-ed English courses decreased leaving the health sciences meta-major. As with the analysis for the full sample, stopping out was a predictor of switching in multiple meta-majors, including humanities/ liberal arts (the largest origin meta-major), social sciences, and public safety. Academic confidence—a self-reported measure of students' confidence in their academic success—predicted leaving the health sciences meta-major, the second largest origin major. Receiving academic advising predicted staying in the humanities/liberal arts and health sciences meta-majors, which likely drives the results in our analysis on the full sample, because these two majors draw the bulk of first-year students. The use of academic advising during the first year of college was associated with a 12- and 10-percentage-point decrease in the probability of switching out of each meta-major, respectively (humanities/liberal arts: $AME = -.117$, $SE = .044$, $p = .010$; health sciences: $AME = -.099$, $SE = .044$, $p = .029$).

We also examined whether institutional characteristics were associated with the probability of meta-major switching at community colleges, primarily as a means of controlling for differences across institutions. We found that the percent of Pell recipients was positively correlated with meta-major switching for students who initially entered the humanities/ liberal arts and public safety meta-majors. Percent non-White was negatively related to switching out of the education meta-major. Average net cost was negatively associated with meta-major switching among students who started in health sciences and enrollment size was positively associated with meta-major switching among students who started in public safety.

Supplemental Analyses on Student Subgroups

To assess whether our model appeared sensitive to the type of student included in the analysis, we also performed additional analyses on subgroups of students based on their educational expectations and attainment/enrollment status. The analyses served as a preliminary exploration of whether educational goals differentially predict meta-major switching and allowed us to consider adjustments to our model specifications (e.g., to include interaction terms, if there were stark differences in some predictors across groups). To begin, Table 6 illustrates the prevalence of meta-major switching across various educational expectations (aiming to earn a certificate/diploma, associate degree, or a bachelor's degree or beyond) and students' attainment/ enrollment status. Meta-major switching was more common among community college entrants with higher educational aspirations than those who aimed to earn a certificate. It was also more common among students who were still enrolled in 2014 and had not yet earned a credential compared with students who had earned a credential and students without a credential who were no longer enrolled.

In our analyses across educational expectations, presented in Table 7, we used the same regression model as in the main results tables, minus the educational expectations measure (which we omitted because it was used to sort students into subgroups). Predictors of meta-major switching looked fairly similar to the overall results from our regression on the full sample across the three educational expectation groups (see Table 5). For example, identifying as a woman was positively related to switching for all three groups, though it was significant only for bachelor's degree aspirants (likely due to lower statistical power among certificate/diploma and associate degree aspirants, which had smaller *N*s). No other patterns across the demographic predictors stuck out to us. We observed similar directions and significance of results to those in the full sample for stopping out and months enrolled. One difference from the main results was that we did not observe a clear relationship between academic advising and meta-major switching for students with associate degree aspirations (however, it negatively predicted meta-major switching for students with certificate/diploma and bachelor's degree aspirations, similar to the main results). We also noticed that receiving career services positively predicted meta-major switching among students with certificate/diploma aspirations, which was not the case in the full sample or in the other subsamples based on educational aspirations. We did not change our model specification in the main paper based on these few inconsistencies, as we acknowledge that there is increased risk of Type I error when performing multiple comparisons; we also did not want to add interaction terms without theoretical justification. Instead, we present the results here for future researchers to consider.

Next, we turn to student subgroups based on attainment/enrollment status (see Table 8). Again, we largely observed the same patterns as those we obtained in the full sample, with a few notable exceptions. Academic advising again was negatively correlated with meta-major switching for all student subgroups, although the results were only significant for those who has earned a credential by 2014, which suggests they may drive the results observed in the full sample. We also noticed that although stopping out and months enrolled both significantly predicted meta-major switching among students who had earned a credential and for those who no longer enrolled, the measures were not significant for students who were still enrolled but had not yet earned a credential. We did not make any changes to the main model based on these findings, given that academic advising, stopping out, and months enrolled were all fairly consistent in the direction of their relationships with meta-major switching across all of the other subgroups. Without a clear theory to drive the inclusion of interaction terms, we decided to keep the model as is. These distinctions may be useful for future inquiries.

Overall, the exercise served to allow us to take some preliminary steps in exploring predictors of meta-majors across subgroups of students—which can inform future research. Given that we largely found similar patterns to those observed in our main results across subgroups of students based on their educational expectations and attainment/enrollment status, the findings bolster support for the model specification we used to produce our main results.

Discussion

There is a pressing need to understand the factors that influence major switching at community colleges given ongoing reforms to align with guided pathways recommendations, which sort students into "meta-majors" with the expectation that colleges will provide structured supports to keep them on that major pathway. A great deal of research has been conducted on major choice and major switching (particularly related to leaving STEM fields) at four-year colleges, but there is very little evidence to inform institutional efforts to improve major persistence among two-year college students. In this study, we used the most recently available nationally representative data to examine patterns of meta-major choice and switching among community college entrants. The findings illustrated that there are high rates of movement between meta-majors (if we had considered major switching between specific majors, the numbers would be even higher). These meta-majors, aligned with meta-majors being implemented at colleges across the country, should include similar majors that would have the same general education and prerequisite coursework. We found that about 40 percent of students switch between meta-majors. This high rate of switching has important implications for students' ability to take appropriate and applicable coursework and to move toward their educational goals.

Among students who switched meta-majors, the most common destination was undeclared. The proportion of undeclared students grew threefold from year 1 to year 3 (the opposite direction we would have expected it to go), with descriptive statistics suggesting that the change was driven largely by students from low-income families, students of color, and women. Among the STEM meta-major, there was a particularly high rate of switching into undeclared, which may indicate that many students leaving STEM struggle to determine another meta-major to transition into.

Our results offer insights into which factors predict students' switch from their first-year meta-major, including variation in meta-major switching across race, gender, and college experiences. The descriptive results illustrated variation in the demographic make-up of initial meta-majors. For example, women were overrepresented in social science, education and health science meta-majors and men were overrepresented in public safety, STEM, and IMAC meta-majors. Switching between meta-majors by year 3 closed some of these gaps but not substantially. Overall, women appeared more likely than men to switch out of their origin meta-major, as shown in the regression on the full sample, but the relationship between gender and meta-major switching appears particularly salient in the STEM regression results. Descriptively, the gender gap in the STEM meta-major closed by 5.3 percentage points between year 1 and year 3, but men still made up 70% of STEM meta-majors. The story is further complicated by our regression results. After controlling for student background, college experiences, and institutional characteristics, identifying as a woman positively predicted switching out of a STEM meta-major. Taken together, this suggests that the STEM meta-major has higher attrition for women than men (though women who leave the STEM meta-majors are being replaced by other women—time will tell if those switches result in degree attainment). Colleges that experience similar patterns to what we observe in the national data may want to examine the climate for women in these fields and build additional support services.

The findings stand to illuminate existing social stratification in processes that occur during college (how students sort into various majors, even after initial major choice) and to inform ongoing reforms at community colleges. Nonpersistence in high-return meta-majors among women and students of color—particularly the loss of women in STEM and Hispanics in business fields—has implications for inequality and may pinpoint the need for additional targeted interventions for retention within competitive majors at community colleges. These disparities are present despite controlling for measures of achievement, suggesting this is not about rigor or ability (often the defense of faculty and staff when they describe high attrition in STEM fields at four-year colleges). The results suggest that there may be parallels in some major switching patterns at community colleges and four-year colleges, particularly for fields such as STEM that are likely to feed into transfer pathways.

Our results also offer some insights about the role some college experiences play in shaping meta-major switching, with implications for ongoing reforms. Academic advising was negatively associated with meta-major switching within the first three years of community college (though, this results appeared most salient in the humanities/liberal arts and health sciences meta-majors, which were among the most prominent meta-majors). This aligns with the guided pathways movement’s emphasis on the role academic advising can play in helping students maintain progress in a given meta-major. Additionally, stopping out was generally associated with meta-major switching, which may suggest that colleges hoping to help student stay on a meta-major pathway need to increase support for students who stop enrollment and then return (perhaps requiring advising sessions when they re-enroll).

Implications for Future Inquiry

Future research should continue to explore major choice and major switching at community colleges. Some of that work will need to explore course-taking patterns and examine programs of study in which students take the majority of their credits, because a student’s program of study and intended major may not align (Jenkins & Cho, 2012). One line of research that could be helpful would be to capture course-taking patterns and major decisions and examine how they align and change over time. At this point, such an endeavor is not feasible with the latest BPS but may be possible with state administrative data if it captures multiple measures of students’ majors (and may be possible with the BPS:12/17 once transcript data are released).

We found little evidence that college characteristics predict major switching, but we see the need for additional inquiry in this area. Ideally, we would include measures at the department level (or within broad fields at the institution), similar to those used in research at four-year institutions (e.g., Griffith, 2010; Price, 2010), to capture faculty and student characteristics within meta-majors to facilitate understanding of demographic representation in that field.

We also encourage additional examination of the link between meta-major switching and college outcomes, like degree attainment and nonpersistence. A recent study uses state administrative data to estimate the impact of major switching on the academic outcomes of community college students in an anonymous state (Liu et al., 2020)—we hope to see similar work in other contexts. Our goal in this study was to establish a benchmark of meta-major choice and switching at community colleges across the nation; an important next step will be continued attention to whether and how switching meta-majors relates to college outcomes and for which students. Our preliminary exploration of predictors of meta-major switching for students with different attainment/enrollment statuses illustrates that the predictors appear similar across students who graduated within three years, those who were still enrolled, and those who were no longer enrolled but had not earned a degree, though some of the small differences we observed might inform future research moving forward.

Implications for Policy and Practice

Meta-majors and other recommendations from the guided pathways movement at community colleges aim to help students identify a clear path toward their desired degree and make it harder for students to veer off structured pathways toward that degree. Our results indicate a high level of switching across meta-majors. This probably means that colleges will need to devote considerable effort to improving the persistence of students in their meta-majors. If colleges implement guided pathways reforms by aligning curricula to be similar within majors comprising a given meta-major, they must also provide advising support and other services to ensure that students pick an initial meta-major that meets their goals and can maintain momentum in that broad field. Colleges that implement the reforms by creating meta-majors without increasing support for meta-major persistence may see little return if students switch between meta-majors at a rate similar to what we observe using national data.

Rather than a piecemeal approach to implementing guided pathways (i.e., adopting of meta-majors without other reforms), colleges might consider a “best process” approach in which administrators, faculty, and staff work together to review programs, processes, and services at each stage of students’ experience at that institution (Jenkins & Cho, 2012, p. 4). This work could include rethinking their practices to help students select an initial major and complete a degree in that field. Our results illuminate high levels of switching into undeclared status at community colleges. This may be indicative of students having selected a major that did not align with their interests or career aspirations. College personnel might also consider how enrollment patterns and advising services play a role in student experiences at their institutions. In our results using national data, stopping out was positively correlated with meta-major switching and academic advising was negatively correlated with meta-major switching.

Ideally, colleges could use institutional data to inform the ongoing changes to their programs, performing similar analyses to those offered here to understand how students select and switch between meta-majors (or major groupings that may align with preferred meta-majors, if they are not yet implementing the reforms) at their college. We recommend colleges start by replicating the descriptive analyses in this study to explore patterns of major switching. If a college finds that a high volume of students are moving from one meta-major to another (where those meta-majors do not have aligned curricula), it may indicate that efforts should be taken to better align the curricula to eliminate unnecessary coursework and/or improve advising to help students identify which broad field they plan to pursue. Performing subsequent regression analyses on meta-majors with a high rates of meta-major nonpersistence could illuminate which student characteristics and college experiences predict switching, controlling for other measures. We expect that shifting patterns of meta-major switching will require a lot of the practical work focused on increased communication—both between faculty in related academic fields to ensure they find common ground in major requirements and between administrators and faculty to identify the best approaches for advising students—and targeting students for additional support (Bailey et al., 2015).

Conclusion

Our study suggests that community college students switch majors at high rates, even between fields that are broadly related. These patterns bolster support for efforts to improve structures and supports to guide students in their major selection and major persistence. We advocate for paying additional attention to the alignment of students' goals and initial major selection (which could reduce major switching) and for further examination of major nonpersistence, both in future research and in practice. Such efforts could improve student success and inform community college reforms across the country.

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Appendix

TABLE A1.

Factor Analysis on Student Involvement on Campus

	M (SD)	Factor Loadings
Factor: Student involvement at community colleges		
• Satisfaction with studies—Satisfaction with studies at college (2012)	4.166 (1.026)	0.799
• Belong at the institution—Indicates whether the respondent felt like a part of the institution in 2012	3.971 (1.114)	0.789
• Interaction with faculty—Indicates whether the respondent felt like having more positive interactions with teachers at the institution in 2012 than negative ones	4.356 (0.914)	0.773
• Interaction with other students—Indicates whether the respondent felt like having more positive interactions with peers at the institution in 2012 than negative ones	4.318 (0.900)	0.748
Cronbach's Alpha		**0.780**

Note. N = 4,250. To capture student involvement on campus, we used measures of academic satisfaction, sense of belonging, and campus interactions. According to Kline6 (2016), the factor loadings indicate direct effects of the student involvement factor on four measures; the measures are highly correlated with the factor. In addition, Cronbach's alpha suggests internal consistency across the four items that measure student involvement (values of .80 and .70 are considered "very good" and "adequate," respectively).

TABLE A2.

Meta-Major Construction (Unweighted)

		2011–2012		2014	
Meta-Major	**BPS Majors[a] (23 categories)**	**n**	**%**	**n**	**%**
Undeclared	Undecided	130	3.1	567	13.4
STEM	Computer and information sciences	3.9	164	3.9	164
	Engineering and engineering technology	6.1	242	5.7	257
	Biological and physical science, science technology	131	3.1	114	2.7
	Mathematics	8	0.2	12	0.3
	Architecture	17	0.4	13	0.3
	Library sciences	3	0.1	2	0.1
	Subtotal	580	13.7	547	12.9
Humanities/ liberal arts					
	General studies and other	567	13.4	379	8.9
	Humanities	168	4.0	132	3.1
	History	4	0.1	9	0.2
	Design and applied arts	53	1.3	48	1.1
	Theology and religious vocations	2	0.1	0	0.0
	Subtotal	794	18.7	568	13.4
Social sciences	Social sciences	40	0.9	44	1.0
	Psychology	108	2.5	111	2.6
	Personal and consumer services	161	3.8	171	4.0
	Communications	52	1.2	63	1.5
	Public administration and human services	107	2.5	103	2.4
	Law and legal studies	36	0.9	32	0.8
	Subtotal	504	11.9	524	12.3
Education	Education	215	5.1	221	5.2
Business	Business	470	11.1	461	10.9
Health sciences	Health care fields	957	22.5	782	18.4
Industry/ manufacturing/ agriculture/ construction	Agriculture and natural resources	49	1.2	49	1.2
	Manufacturing, construction, repair, transportation	301	7.1	284	6.7
	Subtotal	350	8.2	333	7.8
Public safety	Military technology and protective services	245	5.8	242	5.7
Total		4,245	100.0	4,245	100.0

Note. N = 4,250. The BPS 23 majors were defined based on the U.S. Department of Education's Classification of Instructional Programs (CIP 2010).

[a]The BPS included a 23-category self-reported measure of major in the first wave and follow-up (BPS12: majors 23, BPS14: maj14), which we sorted into our meta-major measures (described in the Methods section).

Table A3.

Distribution of Student Characteristics Across Initial Meta–Major in 2011–2012

	Undeclared (%)	STEM (%)	Humanities/ Liberal Arts (%)	Social Sciences (%)	Education (%)	Business (%)	Health Sciences (%)	Industry/ Manufacturing/ Agriculture/ Construction (%)	Public Safety (%)
Gender									
Male	5.9	23.0	23.7	7.3	2.1	14.2	6.2	9.4	8.1
Female	3.5	6.2	24.3	15.0	5.7	9.6	30.8	1.4	3.7
Race									
White	4.9	14.2	26.6	10.6	3.8	10.9	17.7	5.9	5.3
Black	1.3	12.0	19.6	13.7	4.0	14.5	25.0	5.0	4.8
Hispanic	4.9	11.1	22.1	12.4	5.1	12.0	20.0	4.2	8.2
Asian	7.4	23.9	22.8	9.8	0.3	14.8	16.9	1.0	2.9
Other	6.6	23.5	17.7	11.3	5.1	6.9	22.4	4.1	2.4
First–generation college student[a]									
No	4.8	16.6	26.2	13.0	4.0	11.6	14.8	3.9	5.0
Yes	4.4	12.8	23.3	11.1	4.2	11.5	20.9	5.4	6.2
Family income quartile									
Q1	2.2	14.6	19.2	13.2	3.7	11.1	23.9	5.1	6.9
Q2	4.7	14.9	21.4	10.3	4.7	13.1	21.1	5.3	4.5
Q3	7.0	12.0	24.4	11.6	5.0	12.2	17.6	5.1	5.0
Q4	4.5	14.2	31.0	10.8	2.8	10.3	15.2	4.7	6.5
Total %	4.6	13.9	24.0	11.5	4.1	11.7	19.4	5.1	5.7
Weighted N	44,708	135,621	233,757	111,807	39,469	113,780	189,358	49,218	55,918

Note. N = 4,250. Analyses used the BPS analysis weight (WTA000); with the weight, our estimates represent 973,636 in the population. Table presents percentage of students in each category for demographic measures. The total percentage for each row is 100%.

[a]Unweighted N = 3,945 in this measure only; 305 participants answered “don t know” to parents’ highest education.

Table A4.

Changes in Distribution of Student Characteristics Across Meta–Major by 2014

	Undeclared (%) (Δ)	STEM (%) (Δ)	Humanities/ Liberal Arts (%) (Δ)	Social Sciences (%) (Δ)	Education (%) (Δ)	Business (%) (Δ)	Health Sciences (%) (Δ)	Industry/ Manufacturing/ Agriculture/ Construction (%) (Δ)	Public Safety (%) (Δ)
Gender									
Male	15.7 (9.7)	20.4 (−2.6)	16.8 (−6.9)	8.7 (1.4)	2.4 (0.3)	11.7 (−2.4)	5.2 (−1.0)	11.4 (2.0)	7.7 (−0.5)
Female	16.7 (13.3)	7.2 (1.0)	14.9 (−9.4)	15.2 (0.2)	6.7 (1.0)	10.4 (0.8)	23.6 (−7.1)	1.3 (−0.1)	4.0 (0.3)
Race									

	Undeclared (%) (Δ)	STEM (%) (Δ)	Humanities/ Liberal Arts (%) (Δ)	Social Sciences (%) (Δ)	Education (%) (Δ)	Business (%) (Δ)	Health Sciences (%) (Δ)	Industry/ Manufacturing/ Agriculture/ Construction (%) (Δ)	Public Safety (%) (Δ)
White	15.6 (10.7)	14.0 (−0.2)	17.8 (−8.9)	10.9 (0.3)	4.4 (0.6)	10.4 (−0.5)	14.5 (−3.2)	7.1 (1.3)	5.3 (0.0)
Black	13.3 (12.0)	9.9 (−2.1)	15.3 (−4–3)	14.4(0.7)	4.2 (0.2)	12.5 (−2.0)	19.3 (−5.7)	6.2 (1.2)	4.8 (0.0)
Hispanic	20.8 (16.0)	10.5 (−0.6)	12.8 (−9.3)	13.7(1.3)	5.6 (0.4)	11.3 (−0.7)	13.8 (−6.2)	3.6 (−0.7)	7.9 (−0.3)
Asian	8.5 (1.1)	21.5 (−2.4)	13.6 (−9.3)	16.4(6.6)	5.8 (5.5)	16.8 (2.0)	13.6 (−3.3)	1.0 (0.0)	2.9 (0.0)
Other races	14.1 (7.5)	23.3 (−0.2)	12.1 (−5.6)	8.4 (−2.9)	5.0 (−0.1)	5.5 (−1.4)	19.5 (−3.0)	9.0 (4.9)	3.1 (0.7)
First–generation college student[a]									
No	17.8 (13.0)	16.7 (0.1)	17.4 (−8.8)	12.7 (−0.4)	4.2 (0.2)	8.0 (−3.7)	11.9 (−3.0)	7.0 (3.0)	4.5 (−0.5)
Yes	15.6 (11.2)	11.9 (−0.9)	15.6 (−7.8)	12.3 (1.1)	4.7 (0.5)	12.0 (0.5)	16.3 (−4.7)	5.6 (0.2)	6.2 (−0.1)
Family income quartile									
Q1	14.5 (12.3)	13.5 (−1.1)	13.2 (−6.1)	14.0(0.8)	4.8 (1.1)	10.7 (−0.4)	17.6 (−6.2)	5.5 (0.4)	6.1 (−0.8)
Q2	17.0 (12.3)	14.4 (−0.5)	12.3 (−9.1)	12.9 (2.6)	4.2 (−0.5)	12.4 (−0.7)	16.2 (−4.9)	5.5 (0.2)	5.1 (0.5)
Q3	17.4 (10.3)	10.5 (−1.5)	17.4 (−7.0)	11.6(0.0)	5.8 (0.8)	11.0 (−1.2)	13.9 (−3.7)	6.8 (1.7)	5.6 (0.5)
Q4	16.1 (11.6)	14.6 (0.4)	20.3 (−10.8)	10.2 (−0.5)	4.1 (1.3)	10.0 (−0.4)	12.9 (−2.3)	5.9 (1.1)	6.0 (−0.5)
Total %	*16.2 (11.7)*	*13.3 (−0.7)*	*15.8 (−8.2)*	*12.2 (0.7)*	*4.7 (0.7)*	*11.0 (−0.7)*	*15.2 (−4.3)*	*5.9 (0.9)*	*5.7 (−0.1)*
Weighted N	*158,144*	*129,159*	*153,684*	*118,782*	*46,159*	*107,161*	*147,570*	*57,608*	*55,369*

Note. N = 4,250. After applying BPS analysis weight (WTA000), our estimates represent 973,636 in the population. Table presents percentage of students in each category across 2014 meta–majors, followed by the difference (Δ) in that characteristic between the first and third year. The distributional difference illustrates how student characteristics across meta–majors changed over time. Total percentage for each row is 100%.

[a]Unweighted N = 3,945 in this measure only; 305 participants answered “don’t know” to parents’ highest education.

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Table 1.

Definitions and Coding of Variables

Variable	Description and Coding	Mean (SD)
Dependent Variable		
Major switching	Indicates whether the respondent changed a meta–major between first and third years	0.397 (0.489)
Independent Variables		
Background		
Female	Identifies as female	0.557 (0.498)
Race		
White	Identifies as White (reference group)	0.535 (0.499)
Black	Identifies as Black	0.123 (0.343)
Hispanic	Identifies as Hispanic	0.253 (0.432)
Asian	Identifies as Asian	0.046 (0.206)
Other	Identifies as Other race	0.044 (0.209)
Age	Age in 2011	21.570 (7.497)
Married	Married in 2011–2012	0.090 (0.303)
Children	Has children in 2011–2012	0.130 (0.356)
Dependent	Financially dependent on parents	0.713 (0.467)
Logged family income	Total income in 2010 for independent students or parents of dependent students	9.553 (3.180)
Parent education	The highest level of education achieved by either parent of the student as of 2011–2012	
No college	HS or less than HS (reference group)	0.369 (0.489)
Less than 4 years	Vocational/technical training, associate degree, or some college but no degree	0.331 (0.461)
Bachelor's degree	Bachelor's degree	0.162 (0.361)
Master's degree	Master's degree or equivalent	0.070 (0.256)
Doctoral degree	Doctoral degree—professional practice and research/ scholarship	0.019 (0.141)
Educational expectations	Highest degree student expected to earn; derived from BPS 2012	
Certificate/ diploma	Certificate/diploma (reference group)	0.029 (0/167)
Associate degree	Associate degree	0.212 (0.409)
Bachelor's degree	Bachelor's degree	0.436 (0.496)
Advanced degree	Master's or higher degree	0.324 (0.468)
Experiences During College		

Variable	Description and Coding	Mean (SD)
Participation in dev–ed English courses	Indicates whether the student took developmental courses in English	0.189 (0.391)
Participation in dev–ed math courses	Indicates whether the student took developmental courses in math	0.312 (0.444)
First–year college GPA	Cumulative grade point average (GPA) in 2011–2012, standardized to a 4–point scale	2.774 (0.933)
Full–time	Initially enrolled as full–time student	0.432 (0.499)
Involvement on campus	A factor score of four items related to student involvement on campus (see Appendix Table A1 for factor analysis results): Students responded to the following statement on a scale of 1 to 5 (1 means “strongly disagree” and 5 means “strongly agree”): (1) I’m satisfied with my studies at my institution, (2)1 feel that I am a part of my institution, (3) My interactions with my teachers at my institution are more positive than negative, and (4) My interactions with other students are more positive than negative	−0.047 (0.995)
Academic confidence	Indicates the respondent’s confidence in academic success in 2012—A 5–Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree)	2.096 (0.639)
Academic advising	Indicates whether the respondent used academic advising in first year	0.507 (0.500)
Academic support services	Indicates whether the respondent used academic services, such as tutoring or writing center support, in first year	0.236 (0.415)
Career services	Indicates whether the respondent used career services in first year	0.103 (0.311)
Stop–outs	Indicates whether the respondent took at least one (non–summer) term off and returned	0.173 (0.369)
Months enrolled	Continuous measure of total months enrolled since initial enrollment	20.480 (9.881)
Institutional Characteristics		
Enrollment size	Fall enrollment size of institution (in 1000s)	14.980 (11.127)
Percent non–White	Percent of non–White enrollment at college	46.934 (22.327)
Percent Pell Grant recipients	Percent of students at college receiving Pell Grants	40.349 (13.970)
Student:faculty ratio	Total FTE students divided by total FTE instructional staff	23.380 (6.717)
Average net cost	Average net price for students awarded grant or scholarship aid (in $ 1,000s)	7.052 (2.451)
Average faculty salary	Average salary of full–time instructional staff—all ranks (in $l,000s)	62.116 (16.931)
Major Variables		
Meta–major in 2011–2012a	Nine classifications for broad major fields (8 major fields, plus undecided); derived from measure of self–reported major from BPS12: majors23	
Undeclared	Student undecided	0.046 (0.213)
STEM	Science, technology, engineering, and mathematics major—1) computer and information sciences, 2) engineering and engineering technology, 3) biological and physical science, science tech, 4) mathematics, 5) architecture, and 6) library sciences	0.139 (0.339)
Humanities/liberal arts	Humanities and liberal arts major—1) general studies and other, 2) humanities, 3) history, 4) design and applied arts, and 5) Theology and religious vocations	0.240 (0.432)
Social sciences	Social sciences major—1) social sciences, 2) psychology, 3) personal and consumer services, 4) communications, 5) public administration and human services, 6) law and legal studies	0.115 (0.321)
Education	Education major—Education	0.041 (0.197)
Business	Business major—Business	0.117 (0.318)

Variable	Description and Coding	Mean (SD)
Health sciences	Health sciences major—Health care fields	0.194 (0.393)
Industry/manufacturing/agriculture/construction	Industry, manufacturing, and construction major—1) Agriculture and natural resources, 2) manufacturing, construction, repair, and transportation	0.051 (0.222)
Public safety	Public safety major—Military technology and protective services	0.057 (0.234)
Meta–major in 2014[a]	Same categories as meta–majors in first year; enables us to consider meta–major switch between first and third years of college; derived from measure of last major enrolled as of 2014 (majl4 in BPS 2014)	
Undeclared		0.162 (0.360)
STEM		0.133 (0.334)
Humanities/liberal arts		0.158 (0.365)
Social sciences		0.122 (0.328)
Education		0.047 (0.213)
Business		0.110 (0.326)
Health sciences		0.152 (0.366)
Industry/manufacturing/agriculture/construction		0.059 (0.222)
Public safety		0.057 (0.234)

Note. N = 4,250. We used the BPS analysis weight (WTA000) to account for subsampling, unknown student eligibility, and nonresponse. With the weight, our estimates represent 973,636 in the population.

[a]See Appendix Table A2 for detailed breakdown of how we derived our nine meta–majors from the 23 categories from BPS's self–reported major measures.

Table 2.

Distribution of Student Characteristics Within Initial Meta–Major in 2011–2012

	Undeclared (%)	STEM (%)	Humanities/ Liberal Arts (%)	Social Sciences (%)	Education (%)	Business (%)	Health Sciences (%)	Industry/ Manufacturing/ Agriculture/ Construction (%)	Public Safety (%)	Total (%)
Gender										
Male	59.4	76.1	45.5	29.4	23.9	55.9	14.7	85.6	65.2	46.0
Female	40.6	23.9	54.5	70.6	76.1	44.1	85.3	14.4	34.8	54.0
Race										
White	56.5	54.0	58.7	48.9	49.2	49.5	48.2	61.3	49.0	52.9
Black	3.9	11.6	11.0	16.1	13.2	16.7	17.3	13.4	11.1	13.4
Hispanic	26.7	20.1	23.2	27.3	32.0	26.0	26.0	21.1	35.9	25.2
Asian	6.8	7.3	4.0	3.6	0.4	5.4	3.7	0.8	2.2	4.2
Other races	6.0	7.1	3.1	4.1	5.3	2.5	4.8	3.4	1.8	4.2
First–generation college student[a]										
No	27.1	30.7	27.9	28.6	24.8	25.7	19.6	20.0	21.5	25.6
Yes	72.9	69.3	72.1	71.4	75.2	74.3	80.4	80.0	78.5	74.4
Family income quartile										
Q1	12.0	26.3	20.1	28.9	22.8	23.8	30.7	25.2	30.0	25.0
Q2	25.5	26.7	22.2	22.4	29.0	28.0	27.1	26.4	19.8	25.0
Q3	38.3	21.5	25.4	25.3	31.0	26.1	22.6	25.0	21.9	25.0
Q4	24.2	25.5	32.3	23.4	17.2	22.0	19.5	23.4	28.3	25.0
Total %	4.6	13.9	24.0	11.5	4.1	11.7	19.4	5.1	5.7	100.0
Weighted N	44,708	135,621	233,757	111,807	39,469	113,780	189,358	49,218	55,918	973,636

Note. N = 4,250. Analyses used the BPS analysis weight (WTA000); with the weight, our estimates represent 973,636 in the population. Categories within a variable add up to 100% within each column/meta–major.

[a]Unweighted N = 3,945 in this measure only; 305 participants answered “dont know” to parents’ highest education.

Table 3.

CHANGES IN DISTRIBUTION OF STUDENT CHARACTERISTICS WITHIN META–MAJOR BY 2014

	Undeclared (%) (Δ)	STEM (%) (Δ)	Humanities/ Liberal Arts (%) (Δ)	Social Sciences (%) (Δ)	Education (%) (Δ)	Business (%) (Δ)	Health Sciences (%) (Δ)	Industry/ Manufacturing/ Agriculture/ Construction (%) (Δ)	Public Safety (%) (Δ)	Total (%) (Δ)
Gender										
Male	44.4	70.8	49.1	32.9	23.3	49.1	15.8	88.6	62.1	46.0
	(−15.1)	(−5.3)	(3.6)	(3.5)	(−0.5)	(−6.8)	(1.1)	(3.0)	(−3.0)	
Female	55.6	29.2	50.9	67.1	76.7	50.9	84.2	11.4	37.9	54.0
	(15.1)	(5.3)	(−3.6)	(−3.5)	(0.5)	(6.8)	(−1.1)	(−3.0)	(3.0)	
Race										
White	50.8	55.7	59.6	47.1	48.7	50.2	50.7	63.7	49.4	52.9
	(−5.7)	(1.7)	(0.9)	(−1.7)	(−0.4)	(0.7)	(2.5)	(2.3)	(0.4)	
Black	11.0	10.0	13.0	15.9	11.9	15.3	17.1	14.1	11.3	13.4
	(7.1)	(−1.5)	(2.1)	(−0.2)	(−1.3)	(−1.4)	(−0.1)	(0.7)	(0.1)	
Hispanic	32.4	20.0	20.5	28.4	29.7	25.9	23.0	15.2	34.9	25.2
	(5.6)	(−0.1)	(−2.7)	(1.1)	(−2.2)	(0.0)	(−3.0)	(−5.9)	(−1.0)	
Asian	2.2	6.9	3.6	5.7	5.2	6.5	3.8	0.7	2.2	4.2
	(−4.6)	(−0.4)	(−0.4)	(2.1)	(4.8)	(1.1)	(0.1)	(−0.1)	(0.0)	
Other races	3.7	7.4	3.2	2.9	4.4	2.1	5.4	6.4	2.3	4.2
	(−2.4)	(0.3)	(0.1)	(−1.2)	(−0.9)	(−0.4)	(0.5)	(3.0)	(0.5)	
First–generation college student[a]										
No	28.2	32.5	27.8	26.2	23.5	18.6	20.0	29.9	19.9	25.6
	(1.1)	(1.7)	(−0.1)	(−2.5)	(−1.3)	(−7.2)	(0.5)	(9.9)	(−1.6)	
Yes	71.8	67.5	72.2	73.8	76.5	81.4	80.0	70.1	80.1	74.4
	(−1.1)	(−1.7)	(0.1)	(2.5)	(1.3)	(7.2)	(−0.5)	(−9.9)	(1.6)	
Family income quartile										
Q1	22.4	25.5	20.9	28.8	25.6	24.3	29.1	23.3	26.8	25.0
	(10.4)	(−0.8)	(0.9)	(−0.1)	(2.8)	(0.5)	(−1.6)	(−1.9)	(−3.3)	
Q2	26.2	27.1	19.5	26.4	22.0	28.1	26.7	23.3	22.4	25.0
	(0.6)	(0.5)	(−2.8)	(4.0)	(−7.0)	(0.2)	(−0.4)	(−3.1)	(2.6)	

	Undeclared (%) (Δ)	STEM (%) (Δ)	Humanities/ Liberal Arts (%) (Δ)	Social Sciences (%) (Δ)	Education (%) (Δ)	Business (%) (Δ)	Health Sciences (%) (Δ)	Industry/ Manufacturing/ Agriculture/ Construction (%) (Δ)	Public Safety (%) (Δ)	Total (%) (Δ)
Q3	26.7	19.8	27.5	23.8	30.7	25.0	22.9	28.6	24.4	25.0
	(−11.6)	(−1.7)	(2.1)	(−1.4)	(−0.3)	(−1.2)	(0.3)	(3.6)	(2.5)	
Q4	24.7	27.5	32.1	20.9	21.7	22.6	21.3	24.8	26.4	25.0
	(0.5)	(2.0)	(−0.2)	(−2.5)	(4.5)	(0.5)	(1.7)	(1.4)	(−1.9)	
Total %	16.2	13.3	15.8	12.2	4.7	11.0	15.2	5.9	5.7	100.0
	(11.7)	(−0.7)	(−8.2)	(0.7)	(0.7)	(−0.7)	(−4.3)	(0.9)	(−0.1)	
Weighted N	158,144	129,159	153,684	118,782	46,159	107,161	147,570	57,608	55,369	973,636

Note. N = 4,250. Analyses used the BPS analysis weight (WTA000); with the weight, our estimates represent 973,636 in the population. Table presents percentage of students in each category, followed by the difference (Δ) in the reported value between the first and third years in parentheses. Categories within a variable add up to 100% within each column/meta–major.

[a]Unweighted N = 3,945 in this measure only; 305 participants answered “don’t know” to parents’ highest education.

Table 4.

Distribution of Major Switching Between First and Third Years

2011–2012 Major Choice (%)	2014 Major Choice (%)								
	Undeclared	STEM	Humanities/Liberal Arts	Social Sciences	Education Business	Health Sciences	Industry/Manufacturing/ Agriculture/Construction	Public Safety	
Undeclared	59.6	15.9	3.3	5.2	1.1	4.7	4.9	3.6	1.6
STEM	14.1	62.5	4.3	5.3	0.8	2.0	4.3	5.2	1.6
Humanities/									
liberal arts	15.9	6.7	50.9	7.2	2.8	6.2	5.8	2.9	1.5
Social sciences	12.8	4.7	6.7	63.7	2.0	4.0	4.2	0.2	1.6
Education	16.0	1.6	2.3	5.5	64.3	4.8	5.6	0.0	0.0
Business	12.2	3.5	4.4	5.4	2.7	62.9	5.2	1.5	2.1
Health sciences	16.4	4.8	5.0	5.0	2.6	4.2	58.8	1.0	2.2
Industry/manufacturing/									
agriculture/construction	4.8	3.6	5.7	3.7	0.6	2.3	1.0	76.7	1.6
Public safety	12.7	1.4	3.2	2.8	3.7	1.5	2.4	1.3	71.0

Notes. N = 4,250. Italicized % indicates proportion of students who changed majors between 2011–2012 and 2014. The outlined cells highlight students who remained in the same meta-major in 2011–2012 as in 2014. The total percentage for each row is 100%. Analyses used the BPS analysis weight (WTA000); with the weight, our estimates represent 973,636 in the population.

Table 5.

Binary Logit Regression Model Predicting Major Switching

	Each Meta-Major								
	Overall	STEM	H/LA	SS	EDU	BUS	HS	IMAC	PS
Variable	AME (SE)	AME (SE)	AME (SE)	AME (SE)	AME (SE)	AME (SE)	AME (SE)	AME (SE)	AME (SE)
Background									
Female	0.070**	0.165*	0.109*	0.055	−0.168	−0.014	−0.073	0.124	0.066
	(0.022)	(0.066)	(0.044)	(0.057)	(0.093)	(0.054)	(0.056)	(0.099)	(0.061)
Race (Ref. White)									
Black	0.013	−0.083	0.041	0.037	−0.039	0.151	0.032	0.219	0.040
	(0.034)	(0.075)	(0.075)	(0.076)	(0.111)	(0.079)	(0.063)	(0.118)	(0.100)
Hispanic	0.066*	0.007	0.108	0.176*	−0.074	0.198**	0.036	0.115	0.076
	(0.031)	(0.084)	(0.058)	(0.074)	(0.090)	(0.071)	(0.059)	(0.084)	(0.089)
Asian	0.067	0.007	0.059	0.057	—	−0.092	0.063	0.250	−0.252*
	(0.058)	(0.113)	(0.102)	(0.126)		(0.122)	(0.122)	(0.148)	(0.049)
Other races	−0.003	−0.168	−0.083	0.090	−0.167	0.171	0.050	0.075	−0.001
	(0.053)	(0.099)	(0.092)	(0.134)	(0.122)	(0.130)	(0.093)	(0.147)	(0.143)
Age	−0.006*	−0.010	−0.001	−0.004	0.010	−0.008	−0.007	−0.041**	0.001
	(0.002)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.004)	(0.012)	(0.008)
Married	0.031	−0.234	0.024	−0.080	0.217	0.286*	−0.055	0.195	0.056
	(0.054)	(0.139)	(0.096)	(0.191)	(0.137)	(0.122)	(0.082)	(0.139)	(0.140)
Children	−0.002	0.018	0.005	0.131	0.268	−0.101	−0.092	−0.216	0.085
	(0.044)	(0.105)	(0.093)	(0.102)	(0.137)	(0.112)	(0.076)	(0.118)	(0.116)
Dependent	0.000	−0.042	−0.106	0.139	0.230	0.122	0.060	−0.393***	−0.062
	(0.040)	(0.094)	(0.072)	(0.094)	(0.191)	(0.117)	(0.083)	(0.095)	(0.114)
Logged family income	0.006	0.015	0.018*	−0.004	0.020	0.003	−0.003	0.026*	−0.003
	(0.004)	(0.010)	(0.007)	(0.010)	(0.014)	(0.010)	(0.007)	(0.011)	(0.008)
Parent education level (Ref. No college)									

	Each Meta-Major								
	Overall	STEM	H/LA	SS	EDU	BUS	HS	IMAC	PS
Variable	AME (SE)	AME (SE)	AME (SE)	AME (SE)	AME (SE)	AME (SE)	AME (SE)	AME (SE)	AME (SE)
Less than 4 years	0.015	0.046	−0.070	0.138 *	0.023	0.082	−0.032	−0.118	0.190 **
	(0.026)	(0.077)	(0.050)	(0.069)	(0.082)	(0.065)	(0.052)	(0.063)	(0.078)
Bachelor’s degree	0.045	0.050	−0.120	0.111	−0.125	0.301 **	−0.058	−0.085	0.291 *
	(0.037)	(0.078)	(0.068)	(0.099)	(0.105)	(0.102)	(0.067)	(0.081)	(0.144)
Master’s degree	0.074	−0.160	0.091	0.265 *	−0.131	0.057	0.093	−0.078	−0.117
	(0.049)	(0.100)	(0.086)	(0.107)	(0.138)	(0.120)	(0.105)	(0.105)	(0.068)
Doctoral degree	0.037	−0.029	−0.203	0.065	−0.368 *	0.485 ***	0.050	0.044	—
	(0.075)	(0.229)	(0.118)	(0.156)	(0.075)	(0.138)	(0.168)	(0.211)	
Educational expectations									
(Ref. Certificate/diploma)									
Associate degree	0.029	0.222	0.259	0.205	0.041	0.247	−0.155	0.088	−0.228
	(0.064)	(0.148)	(0.135)	(0.094)	(0.146)	(0.213)	(0.097)	(0.058)	(0.233)
Bachelor’s degree	0.062	0.153	0.299	0.197 *	0.123	0.085	−0.140	0.191 *	−0.099
	(0.063)	(0.141)	(0.124	(0.079)	(0.147)	(0.203)	(0.100)	(0.070)	(0.230)
Advanced degree	0.091	0.223	0.269	0.271 *	0.153	0.102	−0.141	0.199 *	0.024
	(0.065)	(0.147)	(0.125)	(0.092)	(0.154)	(0.205)	(0.105)	(0.080)	(0.236)
Experiences During College									
	−0.054	0.042	−0.026	−0.024	−0.092	0.028	−0.132 *	−0.031	0.042
Participation in dev-ed English courses	(0.029)	(0.082)	(0.061)	(0.066)	(0.088)	(0.077)	(0.056)	(0.113)	(0.102)
	0.018	0.042	−0.024	0.030	0.100	−0.024	0.076	−0.095	−0.123
Participation in dev–ed math courses	(0.027)	(0.067)	(0.052)	(0.061)	(0.074)	(0.062)	(0.052)	(0.073)	(0.068)
First-year college GPA	−0.006	−0.025	0.021	0.050	−0.130 *	−0.010	−0.018	0.048	0.034
	(0.013)	(0.032)	(0.025)	(0.036)	(0.041)	(0.031)	(0.028)	(0.038)	(0.039)
Full–time	0.001	−0.038	0.047	−0.007	0.051	0.047	−0.003	−0.092	0.088
	(0.022)	(0.052)	(0.042)	(0.057)	(0.080)	(0.054)	(0.044)	(0.048)	(0.059)
Involvement on campus	−0.012	−0.022	−0.013	0.013	−0.050	−0.012	−0.024	0.037	−0.026
	(0.011)	(0.029)	(0.022)	(0.030)	(0.037)	(0.029)	(0.022)	(0.031)	(0.024)

	Overall	STEM	H/LA	SS	EDU	BUS	HS	IMAC	PS
		Each Meta-Major							
Variable	**AME (SE)**	**AME (SE)**	**AME (SE)**	**AME (SE)**	**AME (SE)**	**AME (SE)**	**AME (SE)**	**AME (SE)**	**AME (SE)**
Academic confidence	0.013	0.038	−0.026	−0.040	−0.012	−0.081	0.155***	−0.006	0.001
	(0.018)	(0.046)	(0.034)	(0.047)	(0.057)	(0.047)	(0.033)	(0.042)	(0.045)
Academic advising	−0.055*	−0.117	−0.117*	0.022	−0.078	0.002	−0.099*	0.020	−0.037
	(0.023)	(0.058)	(0.044)	(0.059)	(0.081)	(0.055)	(0.044)	(0.049)	(0.061)
Academic support Services	0.038	0.111	0.098*	−0.049	−0.048	0.104	−0.017	0.001	−0.002
	(0.027)	(0.075)	(0.050)	(0.064)	(0.093)	(0.074)	(0.051)	(0.074)	(0.076)
Career services	0.049	0.091	0.013	0.101	0.043	0.127	−0.062	−0.029	0.141
	(0.036)	(0.088)	(0.076)	(0.094)	(0.141)	(0.079)	(0.066)	(0.079)	(0.106)
Stop-outs	0.168***	0.127	0.275***	0.221*	0.140	0.020	0.105	0.155	0.180*
	(0.031)	(0.083)	(0.053)	(0.086)	(0.105)	(0.072)	(0.058)	(0.085)	(0.081)
Months enrolled	0.010***	0.009**	0.017***	0.010**	0.003	0.006*	0.005	0.009**	0.000
	(0.001)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)
Institutional Characteristics									
Enrollment size	0.000	0.002	−0.002	−0.002	0.005	0.001	0.001	−0.001	0.008*
	(0.001)	(0.003)	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)
Percent non-White	0.000	0.001	0.000	−0.002	−0.004*	0.001	0.001	−0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Percent Pell Grant recipients	0.001	0.001	0.004*	−0.002	0.003	−0.001	0.000	0.000	0.007***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Student:faculty ratio	0.001	−0.001	0.004	0.003	−0.002	0.004	−0.007	−0.004	−0.003
	(0.002)	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)	(0.005)	(0.004)
Average net cost	−0.006	−0.011	0.012	−0.010	−0.009	−0.005	−0.030**	−0.018	0.006
	(0.005)	(0.011)	(0.009)	(0.010)	(0.017)	(0.011)	(0.009)	(0.011)	(0.014)
Average faculty salary	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sample size	4,250	580	790	500	210	470	960	350	240

Note. N = 4,250. Table presents average marginal effects (AME) and standard errors (SE) for each covariate included in our regression models. Each column represents a separate regression model. The first included the entire sample and the subsequent analyses restricted the sample to students in the given meta-major in 2011–2012. We used eight meta–major categories, which correspond to the abbreviated terms on the columns: (1) STEM = science, technology, engineering, and mathematics, (2) H/LA = humanities/liberal arts, (3) SS = social sciences, (4) EDU = education, (5) BUS = business, (6) HS = health sciences, (7) IMAC = industry, manufacturing, agriculture, and construction, and (8) PS = public safety. While we examined “Undeclared” as a major category in descriptive analyses, it was excluded here due to small sample size, since only 3.1% (unweighted) of students were undeclared in the first year (n = 130). Analyses used the BPS analysis weight (WTA000); with the weight, our estimates represent 973,640 in the population.

* $p < .05$,

** $p < .01$,

*** $p < .001$.

Table 6.

Descriptive Statistics for Meta–Major Switching by Educational Expectations and Enrollment and Graduation Status (Unweighted and weighted)

			Meta–Major Switching			
			Unweighted		Weighted	
Condition	**Subgroup**	**n**	**M**	**SD**	**M**	**SD**
Educational expectations	Certificate/diploma	240	0.224	0.418	0.222	0.417
	Associate degree	1,010	0.306	0.461	0.324	0.468
	Bachelor's or higher degree	3,000	0.404	0.491	0.425	0.494
Attainment and enrollment status	Earned certificate or associate degree	820	0.281	0.450	0.308	0.462
	No credential, still enrolled in 2014	1,570	0.483	0.500	0.522	0.500
	No credential, not enrolled in 2014	1,860	0.316	0.465	0.325	0.468
Total		4,250	0.371	0.483	0.397	0.489

Note. $N = 4{,}250$. Analyses used the BPS analysis weight (WTA000); with weights, population estimate is $N = 973{,}636$.

TABLE 7.

Binary Logit Regression Model Predicting Meta-Major Switching by Educational Expectations

Educational Expectations Variable	Certificate/Diploma AME (SE)	Associate Degree AME (SE)	Bachelor's or Higher Degree AME (SE)
Background			
Female	0.078 (0.050)	0.031 (0.046)	0.082** (0.026)
Race (Ref. White)			
Black	−0.135 (0.076)	0.122 (0.066)	−0.010 (0.039)
Hispanic	0.071 (0.102)	0.106 (0.066)	0.062 (0.036)
Asian	—	0.097 (0.134)	0.065 (0.065)
Other races	−0.120 (0.103)	0.036 (0.123)	0.000 (0.062)
Age	0.001 (0.006)	−0.001 (0.004)	−0.008* (0.003)
Married	0.043 (0.093)	−0.001 (0.095)	0.048 (0.071)
Children	0.031 (0.075)	0.049 (0.077)	−0.010 (0.057)
Dependent	0.174 (0.139)	0.055 (0.081)	−0.023 (0.047)
Logged family income	−0.026 (0.015)	0.009 (0.007)	0.007 (0.005)
Parent education level (Ref. No college)			
Less than 4 years	−0.120 (0.063)	0.028 (0.051)	0.018 (0.031)
Bachelor's degree	−0.154 (0.081)	−0.016 (0.088)	0.064 (0.040)
Master's degree	−0.045 (0.098)	−0.027 (0.109)	0.092 (0.055)
Doctoral degree	−0.025 (0.144)	0.203 (0.160)	0.006 (0.081)
Experiences During College			
Participation in dev-ed English courses	−0.166 (0.093)	0.023 (0.059)	−0.082* (0.035)
Participation in dev-ed math courses	0.052 (0.110)	0.053(0.055)	0.009 (0.031)
First-year college GPA	−0.023 (0.038)	−0.023 (0.028)	−0.001 (0.016)
Full-time	0.039 (0.051)	0.011 (0.043)	−0.001 (0.026)
Student involvement	−0.024 (0.030)	−0.003 (0.022)	−0.015 (0.013)
Academic confidence	0.005 (0.041)	0.003 (0.036)	0.019 (0.022)
Academic advising	−0.100* (0.048)	0.023 (0.046)	−0.071** (0.026)
Academic support services	0.181* (0.086)	−0.019 (0.055)	0.055 (0.032)
Career services	0.463** (0.155)	−0.084 (0.061)	0.069 (0.042)
Stop-outs	0.196* (0.089)	0.233*** (0.066)	0.145*** (0.036)
Months enrolled	0.014*** (0.003)	0.010*** (0.002)	0.010*** (0.001)
Institutional Characteristics			
Enrollment size	−0.005 (0.005)	0.003 (0.002)	−0.001 (0.001)
Percent non-White	0.002 (0.002)	0.000 (0.001)	0.000 (0.001)
Percent Pell Grant recipients	0.003 (0.001)	0.001 (0.001)	0.002 (0.001)
Student: faculty ratio	−0.000 (0.005)	0.002 (0.003)	0.002 (0.002)
Average net cost	0.015 (0.017)	−0.009 (0.009)	−0.006 (0.005)

Educational Expectations			
Variable	Certificate/Diploma AME (SE)	Associate Degree AME (SE)	Bachelor's or Higher Degree AME (SE)
Average faculty salary	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Unweighted N	240	1,010	3,000
Weighted N	28,601	217,397	727,638

Note. Analyses used the BPS analysis weight (WTA000). Table presents average marginal effects (AME) and standard errors (SE) for each covariate included in our regression models. Each column represents a separate regression model for meta-major switch on different subgroups of students based on educational expectations. The regression models restricted the sample to students in the given educational expectations in 2011–2012. We used three educational expectations categories: (1) certificate/diploma, (2) associate degree, and (3) bachelor's or higher degree.

* $p < .05$,

** $p < .01$,

*** $p < .001$.

TABLE 8.

Binary Logit Regression Model Predicting Meta-Major Switching by Attainment/Enrollment Status in 2014

	Attainment/Enrollment Status		
Variable	**Earned Certificate or Associate Degree AME (SE)**	**No Credential, Still Enrolled AME (SE)**	**No Credential, Not Enrolled AME (SE)**
Background			
Female	0.077 (0.045)	0.062 (0.036)	0.073 * (0.030)
Race (Ref. White)			
Black	0.117 (0.094)	0.046 (0.059)	0.001 (0.044)
Hispanic	0.044 (0.080)	0.061 (0.047)	0.088 * (0.044)
Asian	−0.017 (0.115)	0.094 (0.079)	0.127 (0.093)
Other races	0.081 (0.106)	−0.034 (0.101)	−0.010 (0.065)
Age	−0.008 (0.005)	−0.011 * (0.005)	0.000 (0.003)
Married	0.057 (0.101)	−0.115 (0.099)	0.085 (0.065)
Children	0.007 (0.092)	0.072 (0.084)	−0.088 (0.054)
Dependent	0.027 (0.099)	0.000 (0.075)	0.003 (0.050)
Logged family income	0.012 (0.008)	0.011 (0.006)	−0.001 (0.005)
Parent education level (Ref. No college)			
Less than 4 years	−0.018 (0.061)	0.052 (0.046)	−0.007 (0.033)
Bachelor's degree	−0.015 (0.070)	0.014 (0.055)	0.086 (0.057)
Master's degree	−0.128 (0.526)	0.105 (0.084)	0.132 * (0.065)
Doctoral degree	−0.003 (0.146)	0.057 (0.126)	0.083 (0.115)
Educational Expectations (Ref. Certificate/diploma)			
Associate degree	−0.046 (0.097)	0.068 (0.117)	0.044 (0.071)
Bachelor's degree	0.030 (0.099)	0.073 (0.114)	0.095 (0.070)
Advanced degree	−0.029 (0.102)	0.117 (0.116)	0.100 (0.073)
Experiences During College			
Participation in dev-ed English courses	−0.018 (0.072)	−0.008 (0.048)	−0.099 * (0.038)
Participation in dev-ed math courses	0.007 (0.062)	−0.006 (0.043)	0.035 (0.035)
First-year college GPA	−0.043 (0.029)	0.003 (0.024)	0.000 (0.018)
Full-time	−0.024 (0.046)	−0.050 (0.037)	0.044 (0.030)
Student involvement	0.026 (0.025)	−0.015 (0.021)	−0.018 (0.015)
Academic confidence	−0.003 (0.042)	0.046 (0.031)	−0.007 (0.025)
Academic advising	−0.184 *** (0.050)	−0.021 (0.038)	−0.039 (0.031)
Academic support services	0.090 (0.059)	0.030 (0.042)	0.054 (0.041)
Career services	0.074 (0.075)	0.062 (0.059)	0.022 (0.049)
Stop-outs	0.203 * (0.088)	−0.019 (0.053)	0.224 *** (0.050)
Months enrolled	0.007 * (0.003)	−0.005 (0.005)	0.019 *** (0.002)
Institutional Characteristics			

	Attainment/Enrollment Status		
Variable	**Earned Certificate or Associate Degree AME (SE)**	**No Credential, Still Enrolled AME (SE)**	**No Credential, Not Enrolled AME (SE)**
Enrollment size	0.006* (0.003)	0.001 (0.002)	−0.002 (0.002)
Percent non-White	−0.003* (0.001)	0.000 (0.001)	0.001 (0.001)
Percent Pell Grant recipients	0.001 (0.002)	0.003* (0.001)	0.001 (0.001)
Student: faculty ratio	0.002 (0.003)	0.002 (0.003)	0.000 (0.003)
Average net cost	0.010 (0.008)	−0.005 (0.008)	−0.008 (0.006)
vAverage faculty salary	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Unweighted N	820	1,565	1,860
Weighted N	136,851	366,778	470,007

Note. Analyses used the BPS analysis weight (WTA000). Table presents average marginal effects (AME) and standard errors (SE) for each covariate included in our regression models. Each column represents a separate regression model for meta-major switch on different subgroups of students based on graduation and enrollment status. The regression models restricted the sample to students in a given graduation and enrollment status by summer 2014. We used three graduation and enrollment status categories: (1) earned certificate or associate degree by June 2014, (2) had not year earned a credential and still enrolled in June 2014, (3) had not yet earned a credential and no longer enrolled in June 2014.

* $p < .05$,

** $p < .01$,

*** $p < .001$.