Are Changes of Major Major Changes? The Roles of Grades, Gender, and Preferences in College Major Switching*

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Abstract

The choice of college major is a key stage in the career search. Just as workers often change jobs, almost half of college students switch majors at least once. This paper provides the first comprehensive analysis of major switching, looking at the patterns of switching in both academic and non-academic dimensions. Low grades signal academic mismatch and predict switching majors - and the lower the grades, the larger the switch in terms of course content. Surprisingly, these switches do not seem to improve students' grades. When students switch majors, they switch to majors that "look like them": females to female-heavy majors, blacks to black-heavy majors, and so on. Lower-ability women flee competitive majors at high rates, while higher-ability women and men of all abilities are undeterred. Women are far more likely to leave STEM fields and to switch to majors that are less competitive – but not less science- or math-intensive – suggesting that leaving STEM may be more about fleeing the "culture" and makeup of STEM majors than it is about fleeing science and math.

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1 Introduction

College major is one of the most-studied topics in labor economics and the economics of education. Many factors influence the major choice, including potential earnings, peers, course preparation, preferences, and labor market conditions. Almost half of students switch majors during their time in college, suggesting that major choice is best understood as a process (Chen 2013). Despite the huge literature on major choice, however, relatively little is known about these switching patterns and what motivates students to switch majors.

We provide the first comprehensive analysis of major switching among college students, presenting a model of the major choice process and providing rich descriptive evidence on switching patterns. Our fundamental insight is that one can learn about the motivations for major switching by examining the destinations of the switchers. We study the determinants of switching but also the distance (how different the second major is from the first) and direction (how the characteristics of the chosen major change when a switch is made) of major switches. Not all major changes are created equal, as majors differ both in terms of course requirements and non-course characteristics. Some major changes represent "major changes", while others are smaller corrections. We also provide a detailed analysis of STEM (science, technology, engineering, and mathematics) fields, which are of particular policy interest and have high net switch-out rates among women.

Major switching is common; in our data, 37% of college graduates switch majors. One primary reason for this is grades: low grades predict switching majors - and the lower the grades, the "larger" the switch. Surprisingly, however, these major switches do not lead to grade improvement, even if they involve moving to an "easier" major.

We also show that when students switch majors, they move to majors that "look like them": females to female-heavy majors, blacks to black-heavy majors, and so on. Highly competitive majors drive lower-ability women away, while men and higher-ability women are undeterred. These results are consistent with experimental evidence showing that women shy away from more competitive environments.[1]

Women are far more likely to leave STEM majors than men are. While low grades

[1] See Niederle and Vesterlund (2011) for a survey of this literature.

strongly predict leaving STEM, they do not explain any of the gender gap in switching. When women leave STEM, they often move to majors similar in science and math content but different in gender makeup, grading standards, and student ability, such as nursing. This suggests that they are not fleeing STEM because of a lack of competence or because they do not like science. Colleges seeking to retain more women in STEM fields must be concerned about more than just course content or science readiness.

To motivate the empirical analysis, we develop a two-stage model of matching between students and majors. We model students as a vector with two sets of components: abilities and preferences.[2] Majors, similarly, are a vector of academic (course) requirements and non-course characteristics.

Information frictions can lead to initial mismatch between the student and her major, which may induce the student to switch majors. There are two sources of mismatch: academic mismatch and preference mismatch. The switching patterns we observe suggest that both are important.

Other papers have modeled major search as a process (e.g., Arcidiacono 2004, Altonji 1993), but we are the first to provide a detailed empirical analysis of the switching decision as a stage of that process. Our results offer new insights into why and how students switch majors. In understanding how a student arrives at her final destination, this intermediate step is critical.

The detailed focus on major switching also means that we do not study the dropout decision here. In Astorne-Figari and Speer (2018), we consider dropping out and switching majors as two possible responses to struggles. As we show there, men are more likely to drop out, while women are more likely to switch majors and graduate from college. In this paper, we focus on graduates and zoom in on the switching decision, which can tell us much about how students search for the right field of study. Our analysis is thus most relevant for students who are relatively sure of eventually graduating but want to find the best match for college and beyond. This is worthy of its own analysis because of the huge variety in the distance and direction of major switches, suggesting that switches happen for many different reasons.

Our goal in this paper is to provide the first comprehensive analysis of major switch-

[2]By "abilities", we mean the skills, knowledge, and competencies that students have at the time they enter college. These include innate abilities but also parental investments and educational experiences before college, among other factors.

ing. We study switching on a national scale for all college majors, making our results generalizable to the whole population of college students. Our results are consistent with most previous work, but we also provide new results and insights. In particular, we develop the concepts of "distance" and "direction" of switching in our analysis, which help us better understand students' motivations. Those who struggle early in college not only switch majors more, but are likely to switch to very different majors. Women who leave STEM, meanwhile, switch to less competitive, less male-dominated majors than the men who leave STEM majors.

Our analysis includes factors typically studied in the economics literature on college major – e.g., grades and gender differences – but we also incorporate findings from the education and psychology literatures, which emphasize factors like culture of a major and the personality match between student and major. While these things are difficult to observe in data, we develop proxies for them that help us say something about student preferences and major culture.

While our results are merely descriptive and cannot nail down causal effects, they can suggest that some explanations for switching behavior are more likely than others. For example, our results on women leaving STEM fields are strongly suggestive that non-academic factors are more important than academic ones in understanding that issue.

The paper proceeds as follows. Section 1.1 describes the previous literature and our paper's relation to it. Section 2 presents a model of major choice and major switching. Section 3 discusses our data. Sections 4 and 5 present the main results, both for overall switching and switching out of STEM majors. Section 6 concludes.

1.1 Previous Literature

This paper contributes to several different literatures. We extend the approach of the job mobility literature to college major, while contributing to the literatures on major choice, major switching, STEM fields, and gender gaps in major.

In approach, our paper is similar to the extensive literature on job and occupation mobility. While some have modeled and described the entire career (e.g., Neal 1999), others have narrowed in on the switching decision, even studying the distance of occupational switches just as we do for majors (e.g., Poletaev and Robinson 2008, Gathmann and Schoenberg 2010).

For those who attend college, the major choice process is a key stage of the career search. Neal (1999) analyzes career search as a matching process in which workers search for a good job match. A poor match will lead to the worker changing employers and/or occupations.[3] Neal (1999) observes that college graduates change careers less frequently than less educated workers, suggesting that college allows a student to search over careers prior to entering the labor market. Thus, changing majors can be seen as a pre-labor market form of job mobility.

Researchers have long recognized the choice of major as an important determinant of a worker's job and earnings prospects. Many factors influence major choice, including earnings returns (Berger 1988, Paglin and Rufolo 1990), preferences for different work environments and lifestyles (Easterlin 1995, Arcidiacono 2004), parents' characteristics (Ware, Steckler and Leserman 1985), the impact of peers and advisors (Ware and Lee 1988), and economic conditions (Blom, Cadena and Keys 2017).

A large literature also looks at gender gaps in college major, which are substantial and contribute to the male-female wage gap (Dickson 2010, Brown and Corcoran 1997). Women are especially underrepresented in STEM fields.

Gender gaps in major choice could be driven by differences in preparation (Speer 2017), although most papers emphasize that other factors are more important. Women may shy away from competitive environments (Niederle and Vesterlund 2011, Buser, Niederle and Oosterbeek 2014). The gender of the professors may also matter (Carrell, Page and West 2010), or may have little to no effect (Hoffmann and Oreopoulos 2009, Price 2010, Griffith 2010). The gender and ability composition of first-year classes can also impact major choice (Feld and Zölitz 2017, Fischer 2017). Finally, women may be more responsive to grades than men are, discouraging them from studying difficult fields like STEM and economics (Ost 2010, Owen 2010, Rask and Tiefenthaler 2008).

A few other papers have studied major switching.[4] Altonji (1993) and Arcidiacono

[3]Pavan (2011) and Yamaguchi (2010) explore this matching process with structural models. More recently, Guvenen et al. (2015) propose a measure of the skill match between a worker and an occupation and find that workers are rewarded for finding a job that matches their skills.

[4]Major switching is particularly relevant in the United States, because American students may typically switch majors without switching institutions or going through the admissions process again. This makes the cost of switching relatively low.

(2004) study major choice under uncertainty about ability and outcomes, and students may change majors when they acquire new information. Stinebrickner and Stinebrickner (2013) find that students revise their beliefs about their own abilities in response to grades, leading some students to leave difficult majors. Bettinger (2010) provides summary statistics on the common destinations of STEM leavers and shows that even many students of high pre-college ability leave STEM fields.

Our paper is also related to Hsu (2017) and Kugler, Tinsley and Ukhaneva (2017), who each use administrative data from single universities to study how students respond to grade signals in choosing majors. Hsu (2017) finds that students are deterred from leaving majors they are poorly matched with by the progress they have already made in completing the course requirements. Kugler et al. (2017) focus on gender differences in switching behavior and sensitivity to grades and find that women are more likely to leave male-dominated majors in response to poor grades. Factors like the gender of faculty members and economic returns to the major have little effect on this decision. Neither paper focuses on the destination majors or the "distance" or "direction" of major switches, which is one of our chief contributions.

Finally, the education and psychology literatures have also contributed to the study of major matching and STEM attrition. In education, Seymour and Hewitt (2000) and Brainard and Carlin (1998) use qualitative survey data to show that both academic and non-academic factors influence the decision to leave STEM fields. The psychology literature emphasizes the match between a student's personality and the environment or culture of the major (Holland 1966; Smart, Feldman, and Ethington 1999). We take these ideas seriously and include the notion of personality matches and preferences in our model and empirical analysis. Although we cannot observe personality, our findings can tell us something about the preferences of students and the ways they might be mismatched with their majors.

2 Model

In this section, we present a two-period matching model of college major choice that allows for major switching. The model will motivate our data construction and empirical analysis and help us interpret our results, but we will not estimate the model or test all of its predictions. In Section 2.5, we will summarize the model and discuss how it relates to our empirical work.

In the first period, students choose a major based on the information that is available to them at college entry. At the beginning of the second period (say, after one or two years of college), students learn some new information, and have the option of switching majors. Students experience disutility from choosing a major that is incompatible with their abilities and preferences in each period. While our model describes the entire major choice process, we will focus mostly on the switching decision.

2.1 Students and Majors

A student who enters college is represented by a vector s that is partitioned into two components: abilities (s^x) and preferences (s^θ). Ability is J-dimensional and represents the student's competencies in various subjects, such as math, humanities, and science. Preferences, which are K-dimensional, refer to a student's preferences over non-course aspects of a college major, such as competitiveness, grading standards, or demographics of the major.[5] The s^θ components represent students' ideal value of each major characteristic. A student's preferences stay constant throughout college.

A major is also a vector m with two components. The first component, m^x, denotes the course requirements to complete the major in each of the J categories of abilities. The second component m^θ is K-dimensional and represents the non-course characteristics of the major.[6]

To be clear, m^θ represents the actual non-course characteristics of the major, while s^θ represents the student's preferences about those characteristics. For example, for a θ characteristic like gender makeup, s^θ tells us the student's ideal gender makeup, while m^θ tells us the actual gender makeup of the major. Because students have different preferences over these characteristics, they will have different preference rankings of majors.

We make two assumptions that are worth mentioning. First, majors are "large"

[5]It is possible that all students dislike a certain characteristic, like difficult grading standards. Differences in preferences for these types of characteristics can be thought of as representing variation in how much students dislike that characteristic.

[6]To be precise, $s^x, m^x \in \mathbb{R}^J$ and $s^\theta, m^\theta \in \mathbb{R}^K$.

enough that their θ characteristics are not affected by students' choices. If a female student chooses a certain major, she does not alter the gender makeup of the major.[7] Second, we assume for simplicity that students' preferences are single-peaked. The closer the major is to the student's ideal, the happier the student is.[8]

Given our definitions of students and majors, and assuming full support of majors, for each student there is an ideal major that matches both the student's abilities and preferences on all components.

The match may matter for a number of reasons. For the academic (x) match, a better-matched student may perform better in classes (which may have a return in the labor market), may be more likely to graduate, and may be more enthusiastic about the material. For the preference (θ) match, a better-matched student will enjoy her major more and feel more comfortable and confident due to the major environment matching her own personality and preferences, as emphasized in the psychology literature (Smart et al. 1999).

Frictions arise due to information inaccuracy at the time of initial decision making. For simplicity, we choose two sources of inaccuracy to focus on. First, students imperfectly observe their own abilities s^x, having only beliefs given by $\hat{s}^x$, where $\hat{s}^x$ is normally distributed around the true abilities s^x. These beliefs may come from high school grades, SAT scores, and other pre-college factors.[9] We will call a student's initial beliefs about her abilities $\hat{s}^x_0$. Students will then update their beliefs using Bayes' Rule to $\hat{s}^x_1$ as they acquire new information, as described below.

Second, at college entry, students cannot observe the non-course components m^θ of majors. Instead, for each major, they have a vector of prior beliefs $\hat{m}^\theta_0$ about these

[7] One potential threat to this assumption is peer effects: one student switching may induce others to switch, which could eventually alter the major's makeup. However, Sacerdote (2001) does not find any evidence of important peer effects in major choice.

[8] We find suggestive evidence supporting this assumption. For double-majors, the two majors they choose are "closer together" (as defined in Section 3) than randomly chosen majors would be, suggesting that students' second choices are similar to their first. A recent paper by Kirkeboen, Leuven and Mogstad (2016), studying Norwegian college applicants, finds that some students' second field choices are "far away" from their first. However, in contrast to the United States, Norwegian students apply to a field and institution simultaneously, so it is difficult to apply lessons from this directly to our analysis. Colleges differ in quality, location, and culture, and preferences over these things are conflated with preferences over majors.

[9] There are many reasons why students' beliefs may not be accurate upon college entry. For example, they may judge their ability against their high school classmates, not realizing that this sample is not representative of the population (Murphy and Weinhardt 2016).

non-course components, which represent the student's "stereotype" of each major's characteristics. Beliefs will be correct in expectation, but students' actual experience in a major may not match their prior beliefs. For these two reasons, students may be mismatched with the major they first choose.[10]

If a student is mismatched with her major, she will experience disutility from being mismatched. The disutility of academic mismatch is equal to the distance between the major requirements m^x and the student's beliefs about her own abilities $\hat{s}^x$, denoted by $D(m^x, \hat{s}^x)$. Similarly, the student may be mismatched on preferences, with the disutility denoted by the distance $D(m^\theta, s^\theta)$.[11]

A student who enters college will initially choose the major that she *believes* will be her perfect match on both course and non-course components. That is, she will choose $m^* = (m^{*^x}, m^{*^\theta})$, where $m^{*^x} = \hat{s}_0^x$ and her beliefs about m^{*^θ} match her preferences s^θ.

2.2 Major Switching

After the first period, students receive two types of new information. First, they observe the true non-course characteristics m^θ of all majors (including their first-period choice m^*). This could come from their experience of actually trying out different classes and also observing the choices of their peers.[12] Second, students observe their first-period grades g^x, which are a new signal of their own J abilities. Students update their beliefs about their own abilities according to

$$\hat{s}_1^x = \lambda g^x + (1 - \lambda)\hat{s}_0^x \tag{1}$$

where λ is the precision of the grades signal relative to the precision of the prior belief. The term $\hat{s}_1^x$ denotes a student's second-period beliefs about her own abilities.

[10] While a student may also not know the course requirements m^x for all majors, these are easier to learn, as they would be readily available in the course catalog or on the department's website. Meanwhile, the true m^θ components – such as the gender makeup of the major or how competitive it is – are difficult to observe without experiencing the major in the classroom.

[11] Note that both types of mismatch likely affect the student both in college and in the labor market after college, as the student's future occupation with a degree in major m is likely to use similar skills and have a similar culture to major m. Thus, choosing a major based on these match components is not short-sighted.

[12] This is equivalent to a situation where students receive a perfectly precise signal about non-course characteristics at the end of the first period and update their beliefs to match the new signal.

After students observe this new information, they may realize they are mismatched with their major either on abilities or on preferences. Students have the option to switch from major m^* to major $\tilde{m} \neq m^*$ at a cost given by the "academic distance" between the old major m^* and the new major $\tilde{m}$, $D(m^{*^x}, \tilde{m}^x)$. This cost occurs because some of the courses from the old major will not be counted towards the new major, and the new major will also have some new course requirements that were not met by the old major. The bigger the overlap in course requirements between the new and the old major, the lower the cost of switching majors, and *vice versa*. Switching from biology to physics would likely have a lower cost than switching from biology to history. The cost is not related to the distance between the old and new majors in terms of θ.

If a student chooses to stay in major m^*, expected disutility conditional on second-period beliefs about own ability will be given by the following expression, which for simplicity is separable in the x and θ components:

$$\alpha_x D(m^{*^x}, \hat{s}_1^x) + \alpha_\theta D(m^{*^\theta}, s^\theta) \tag{2}$$

where α_x and α_θ are the sensitivities to abilities mismatch and preference mismatch, respectively.

If the student chooses to switch majors, the new major $\tilde{m}$ minimizes expected disutility of switching majors conditional on her new beliefs, given by the following expression:

$$\alpha_x D(m^x, \hat{s}_1^x) + \alpha_\theta D(m^\theta, s^\theta) + \alpha_c D(m^{*^x}, m^x) \tag{3}$$

where $\alpha_c > 0$ is the sensitivity to major-switching cost.[13]

Therefore, a student will choose to switch majors whenever Expression (3) is greater than or equal to Expression (4) evaluated at $\tilde{m}$. Rearranging terms, a student will switch majors if

$$\alpha_x \Big[D(m^{*^x}, \hat{s}_1^x) - D(\tilde{m}^x, \hat{s}_1^x) \Big] + \alpha_\theta \Big[D(m^{*^\theta}, s^\theta) - D(\tilde{m}^\theta, s^\theta) \Big] \geq \alpha_c D(m^{*^x}, \tilde{m}^x) \tag{4}$$

[13] Variation in the sensitivity to major-switching costs could come from variation in students' patience or value of time, as a large switch could leave the student in college for an extra year (Wright 2016).

From this expression, we can see that the probability of switching depends on several factors.[14] First, lower grades signal academic mismatch and lead to a higher probability of switching majors. If grades are low, $D(m^{*^x}, \hat{s}_1^x)$ is larger, and thus the left side of the expression is larger.

Second, switching depends positively on the degree of initial preference (θ) mismatch $D(m^{*^\theta}, s^\theta)$. The more mismatched a person is on non-course characteristics, the more likely she is to switch majors. Third, those with higher sensitivity to being mismatched (higher α_x and/or α_θ) are more likely to switch majors.[15]

Given our simplifying assumption that the switching cost is not related to the change in non-course (θ) characteristics, the new major $\tilde{m}$ will always be the student's optimal major choice in terms of θ: $\tilde{m}^\theta = s^\theta$. In terms of course requirements (x), there is a cost of switching, which means that the student may not choose to move "all the way" to her optimal major in terms of courses ($\tilde{m}^x = \hat{s}_1^x$).

2.3 Distance of Switching

We can rewrite Expression (5) as

$$D(m^{*^x}, \tilde{m}^x) \leq \frac{\alpha_x}{\alpha_c}\Big[D(m^{*^x}, \hat{s}_1^x) - D(\tilde{m}^x, \hat{s}_1^x)\Big] + \frac{\alpha_\theta}{\alpha_c}\Big[D(m^{*^\theta}, s^\theta) - D(\tilde{m}^\theta, s^\theta)\Big] \qquad (5)$$

The term on the left-hand side is the "academic distance" of a switch from major m^* to major $\tilde{m}$. The term inside the first bracket represents the expected improvement in abilities match resulting from the switch, and the term in the second bracket represents the improvement in preference match resulting from the switch. The ratios $\frac{\alpha_x}{\alpha_c}$ and $\frac{\alpha_\theta}{\alpha_c}$ represent how much more in switching costs the student is willing to tolerate in order to improve her match in terms of abilities and culture respectively.

The larger the mismatch in the initial major, the "larger" the switch that the student is willing to take with a new major, weighted by the student's willingness to

[14] More precisely, we are discussing the probability of switching to major $\tilde{m}$, where $\tilde{m}$ is the major that minimizes Expression (3).

[15] We can see this in Expression (4) because the terms in brackets ($D(m^{*^x}, \hat{s}_1^x) - D(\tilde{m}^x, \hat{s}_1^x)$ and $D(m^{*^\theta}, s^\theta) - D(\tilde{m}^\theta, s^\theta)$), representing the improvements in match, must be greater than or equal to zero. We explain why these terms must be nonnegative in Section 2.4.

bear the major-switching cost in order to improve each type of mismatch. The larger the initial academic mismatch, the greater distance the student is willing to move. If a student is only slightly mismatched academically, she has little to gain from switching majors, and if she does switch, the switch will be small (i.e., to a major with similar course requirements as the initial major). Given that low grades are how academic mismatch is observed, lower grades should lead to larger major switches. Students who perform poorly in their first major should make a "major change", finding a major quite different in course content terms from their initial major choice.[16]

2.4 Direction of Switching

Finally, we are interested in the "direction" of major switching. Direction refers to the change in individual characteristics from the initial major to the final major when the student switches majors. For example, does the student switch toward a major with more or fewer math requirements? Given the assumptions of the model, will students who switch move toward better matches, toward worse matches, or is it unclear?

Intuitively, the answer to this question is obvious: if a student switches majors, she will switch to a major that is a better match for her both in the course (x) and preference (θ) components.[17] With full support of majors, a student will never move to a worse academic match, as there is always the option of at least staying where she currently is. Also, since there is no cost of switching in the preference component, the new major will always be her perfect match in terms of θ.[18]

Because matches improve with switches, grades should improve when students switch majors. Also, while we cannot observe preferences in our data, switches made by students should *reveal* something about their preferences.

[16] While we are the first to explicitly model and implement empirically the distance between majors, the same logic is implied by models that allow learning about student ability to be correlated across majors (Altonji, Arcidiacono and Maurel 2016).

[17] A full proof of this intuitive assertion is simple to construct and available upon request.

[18] In reality, because there is not full support of majors, students may face a trade-off between improving their course and preference matches, and thus not all major switches will be improvements in both dimensions. Even in this case, though, the prevailing pattern of switches should still be toward better matches along both dimensions.

2.5 The Model and the Empirics

The model, though stylized and simple, contains a few testable implications and others that are not directly testable. We will look broadly at four things: the probability of switching, the distance of switching, grade improvement from switching, and the direction of switching.

Major switching should depend negatively on early-college grades, which is testable with the right data. It should also depend positively on initial preference mismatch and sensitivity to mismatch, which is not directly testable.

Regarding direction, students should be moving to better matches, which implies that grades should improve after a major switch. We will test this prediction. Though we have not discussed course-specific grades (and do not have them in our data), the logic of the model implies that higher grades in a particular discipline would lead a student to choose a major that requires more of that discipline (and *vice-versa*). For instance, good grades in math may push a student toward a more math-oriented major. We will look at this to the degree we can, given our data.

Regarding distance, students with lower grades should make larger academic switches, and grades should improve improve more the larger the major switch. These predictions are testable, as we have panel data on college grades and major choice, and will develop a measure of distance between majors.

On preferences, we will describe the switching patterns in the data and attempt to learn something about students' preferences from those patterns.

In addition, there are things left out of the model for simplicity that we will be able to look at empirically. For instance, while students in the model choose their major based on their relative abilities in different subjects, in reality students also differ by their overall level of cognitive ability. This may be correlated with students' preferences over non-course characteristics and ability to handle competitive majors. We will include a variable for the level of cognitive ability in our empirical analysis, despite the model dealing only with relative abilities.

3 Data and Measurement

Our primary data source is the National Longitudinal Survey of Youth 1997 (NLSY). The NLSY is a nationally representative panel data set of 8,984 individuals born between 1980 and 1984, who were surveyed annually from 1997 to 2011 and biennially since 2011. It contains standard demographic information as well as a measure of cognitive skills, the AFQT score.[19]

A key advantage of the NLSY is that it contains a detailed account of the college experiences of respondents. For each college attended in each term, respondents are asked their major field of study and their grade point average. It is thus straightforward to construct a time series of majors and GPAs for each respondent.

We record the first reported major (not counting "No major") and the final reported major before graduation.[20] We call it a major switch if the two are different.[21] The switching rates we measure are similar to national averages reported by the Department of Education (Chen 2013), suggesting that the major reports are reliable and do not merely represent guesses on the student's part.[22]

We define "early GPA" as the average GPA in the first two years of college, and "late GPA" as the average GPA in the last two years of college. This approximates the GPA before and after switching, as the average time of switching is after about 1.5 years of college.[23] We use this definition, rather than using before-switch and after-switch GPAs, to maintain a consistent definition of early and late GPA for switchers and non-switchers. The weakness of our GPA data is that the grades are not linked to specific courses or subjects. We do not know if a student reporting an engineering major, for instance, is mostly taking engineering courses in year one or taking a wide

[19]The Armed Forces Qualifying Test (AFQT) was given to survey respondents in 1999. In addition to measuring cognitive ability, the AFQT may be correlated with students' preferences.

[20]Note that majors are self-reported and do not necessarily represent a major that the student has officially declared.

[21]Defining switching for double majors (about 15% of the sample) is difficult. If a student reports an initial double major, it is not a switch if she finishes in either of those majors, even if she adds or subtracts a major along the way. A student who adds a second major but keeps her original major is also not a switcher. For measuring the distance and direction between first and last majors for double-majoring switchers, we take the majors reported as the primary major in each case.

[22]In our data, 90% of students report three or fewer different majors in college.

[23]This average does not differ by gender. All of our results are robust to different definitions of early and late GPA. Results are also similar when we compare those who switched early in their college career (the first year) with those who switched in year two or later.

variety of courses. It is likely, however, that students are taking *more* courses in their reported major than they are in other majors, and thus grades are giving information – though imprecise – about ability in that major.

Table 1 shows summary statistics for our sample. In our sample of college graduates, 37% of graduates switch majors, and the switch-out rate is similar for STEM fields. Note that "switch out of STEM" does not include those who switch from one STEM field to another. In total, 45% of those who start in STEM switch majors, with 36% switching out of STEM and 8% switching within STEM. Grades improve on average as students go through college. AFQT is standardized by the quarter-year of birth.[24]

The course content portion of a major (m^x) is a vector of course requirements. We get this information from the Baccalaureate and Beyond data. Each major is matched with the average number of credit hours taken in each field by students with that major. For example, a mathematics major takes an average of 30 math credits (making it the most math-intensive major), 13.7 science and engineering credits, and 14.3 social science credits. The course categories we use to construct m^x are mathematics, foreign language, business, humanities, science/engineering, social science, education, and other.[25]

Non-course characteristics (m^θ) include a major's grading standards, competitiveness, and race and gender makeup. These measures are meant to proxy for the "culture" of the major, which we cannot observe directly. We would like school-major-level data on these characteristics, but these data do not exist. Instead, we use major-level national averages.[26]

The race and gender makeup of the major, which could potentially proxy for com-

[24]We include all students who graduated with a bachelor's degree. Our results are similar when including those who attended a four-year college but did not graduate. While the dropout decision is also of interest and is linked to the switching decision – it could be viewed as a substitute for switching majors for some students – we have analyzed dropouts and switchers together in Astorne-Figari and Speer (2018). Dropping out is also likely more complex than the decision to switch majors, as it involves academic factors (Stinebrickner and Stinebrickner 2014) but also things like credit and financial constraints, personal and emotional issues, and lack of parental support (Gerdes and Mallinckrodt 1994). These factors are beyond the scope of the model we use here.

[25]See Speer (2017) for more details on these course measures. The course data is given at the level of 51 major categories, so we map the NLSY major options into those 51 categories. As there are fewer than 51 major categories in the NLSY, this is a one-to-one match with some of the 51 majors not used.

[26]We have also experimented with "adjusting" these national averages by the characteristics of the school. This does not alter our results.

Table 1
Summary Statistics

	n	Mean	St. Dev.	Min	Max
Female	1662	0.58	0.49	0	1
Black	1662	0.15	0.36	0	1
Hispanic	1662	0.12	0.32	0	1
Asian	1662	0.04	0.20	0	1
Early GPA	1662	3.16	0.50	0.95	4.00
Late GPA	1603	3.26	0.45	1.45	4.00
Change in GPA	1603	0.11	0.43	-2.23	2.40
AFQT	1662	0.03	0.99	-2.80	1.36
Major switch	1662	0.37	0.48	0	1
First major STEM	1662	0.25	0.43	0	1
Switch out of STEM	413	0.36	0.48	0	1
Among major switchers (in standard deviations):					
Grading standards change	618	-0.07	1.15	-3.17	2.94
SAT math change	618	-0.06	1.34	-3.54	3.50
Male pct change	618	-0.05	1.31	-3.77	3.32
White pct change	618	0.07	1.35	-4.10	3.32
Black pct change	618	0.06	1.38	-4.37	4.64
Hispanic pct change	618	0.13	1.46	-4.50	4.28
Asian pct change	618	-0.13	1.28	-3.67	3.99

Note: The full sample includes all students who graduated from a four-year college and had a valid AFQT score. Early and late GPA are the average GPA in the first two and last two years of college, respectively. SAT math is the average SAT math score in the major. Grading standards are the difference between the major's SAT composite score rank and its GPA rank. All variables in the bottom panel (SAT math, male percentage, etc.) are measured in standard deviations based on national averages calculated from the American Community Survey or Baccalaureate and Beyond.

petitiveness and other aspects of the major's "culture", are calculated using the American Community Survey (Ruggles et al. 2010).[27] We calculate the national percentage of graduates from a major who are white, black, Hispanic, and Asian, as well as the

[27]The male share of a major may proxy for competitiveness, as there is ample evidence that men are more competitive on average than women (Niederle and Vesterlund 2011). As we show later, Asian share is highly correlated with the male share and average test scores, so this may also proxy for competitiveness of the major.

percentage that are male and female, using the ACS 2003-2008 graduation cohorts to match the NLSY respondents' ages.[28]

Another proxy for competitiveness is the average SAT math score in the major, which we get from the Baccalaureate and Beyond restricted-use data. There are majors with moderately high SAT math scores that are not generally thought of as competitive (e.g., philosophy), but these are the exception rather than the rule. Still, this is an imperfect proxy for competitiveness.[29]

Finally, we create a measure of grading standards in each major. While differences in grading standards across fields have been shown to influence major choice (Minaya 2017), there is no obvious way to measure these standards. Grades pick up information about standards but also student ability. We instead create a new measure of grading standards from the Baccalaureate and Beyond data. We rank the majors by composite SAT scores and also by average GPA. The difference in the two ranks is our measure of grading standards. Majors that rank near the top of SAT scores but near the bottom of GPA (e.g., engineering) have the highest (most difficult) grading standards by our measure, while those with high GPAs relative to SAT scores (e.g., education) have the lowest (least difficult) standards.[30]

Table 2 shows a selection of characteristics for our college majors, in standard deviations for ease of comparison. Nursing is the most female major (90% female), while engineering is the most male major (78% male). Agriculture and computer science are the most white (88%) and least white (59%) majors, respectively. We cannot show the SAT math scores or grading standards due to the use of restricted data, so instead we show the majors' rank in those categories. STEM majors, especially engineering and mathematics, tend to be high-SAT and high in grading standards, as suggested in Rask (2010).

[28]We map ACS majors into the 51 B&B categories using a many-to-one crosswalk we construct.

[29]We have also used an SAT/ACT composite score instead of SAT math scores, which gives similar results.

[30]Of course, there are many other relevant characteristics of a major that we do not observe, including its family-friendliness, the gender makeup of its faculty, and its returns in the marriage market. We have also calculated the specificity of the major according to the occupations its graduates enter, a measure used by Altonji, Blom and Meghir (2012), but the patterns in the data regarding this measure do not add much to the analysis.

Table 2
Major Characteristics, in Standard Deviations

	Non-Course Measures (m^{θ})							Course Measures(m^{x})						
Major	SAT M rank	Grading rank	% Male	% White	% Black	% Asian	% Hispanic	Math	For. Lang.	Humanities	Business	Sci/Engin	Soc. Sci.	Educ
Engineering	1	3	2.02	-1.64	-0.95	2.38	-0.53	1.55	-0.63	-0.83	-0.21	3.00	-1.05	-0.51
Mathematics	2	4	0.70	-0.25	-0.89	1.12	-1.16	4.50	-0.02	-0.21	-0.22	-0.03	-0.67	0.42
Economics	3	7	1.30	-0.56	-0.46	1.04	-0.60	0.17	0.20	0.02	1.44	-0.49	1.32	-0.48
Public admin/law	4	15	-0.22	-1.04	1.92	-0.31	1.49	-0.52	-0.50	-0.55	0.56	-0.67	-0.16	-0.51
Architecture	5	17	0.80	-0.26	-0.92	0.33	0.86	-0.12	-0.53	-0.79	-0.54	-0.29	-0.92	-0.55
Biological sciences	6	5.5	-0.12	-0.92	-0.15	1.35	-0.73	0.21	-0.09	-0.31	-0.52	2.63	-0.70	-0.30
Area studies	7	20	-0.68	-0.94	0.84	-0.07	1.77	-0.39	0.89	0.87	-0.34	-0.49	1.22	-0.31
Computer science	8	11	1.93	-2.32	-0.04	2.90	-0.98	1.24	-0.53	-0.56	0.87	-0.19	-0.76	-0.50
International relations	9	1	-0.37	0.16	-0.77	-0.01	0.44	-0.46	1.39	0.82	-0.22	-0.59	1.75	-0.52
Philosophy/religion	10	9	1.19	1.57	-1.13	-0.83	-0.89	-0.53	0.20	1.47	-0.53	-0.53	-0.19	-0.11
Agriculture	11	2	0.45	2.11	-1.34	-1.00	-1.69	-0.17	-0.74	-0.91	1.33	0.44	-0.79	-0.43
History	12	10	0.78	1.60	-1.03	-0.94	-0.81	-0.46	0.55	0.30	-0.45	-0.51	1.93	0.07
Foreign language	13	18.5	-0.79	0.39	-1.22	-0.50	1.51	-0.32	4.48	2.54	-0.27	-0.46	-0.31	0.27
Political science	14	5.5	0.52	0.30	0.04	-0.52	0.45	-0.43	0.34	0.37	-0.34	-0.50	2.14	-0.42
Art history/fine arts	15	24	-0.60	0.38	-0.58	-0.20	0.11	-0.50	0.04	1.12	-0.50	-0.46	-0.73	-0.09
English/literature	16	16	-0.59	0.53	-0.15	-0.45	-0.14	-0.41	0.40	2.97	-0.48	-0.51	-0.32	-0.01
Interdisciplinary science	17	25	-0.27	-0.71	0.69	0.37	0.23	-0.05	-0.41	-0.25	-0.27	0.36	-0.51	0.97
Earth/physical sciences	18	8	0.82	0.11	-0.81	0.79	-1.37	0.53	-0.25	-0.63	-0.49	2.59	-0.46	0.06
Other med/health services	19	23	-0.08	-0.41	0.31	0.41	-0.27	-0.37	-0.63	-0.87	-0.42	0.33	-1.01	-0.23
Business	20	12	0.31	-0.08	0.33	-0.04	-0.02	-0.15	-0.55	-0.65	4.40	-0.62	-0.56	-0.46
Psychology	21	22	-1.08	-0.19	0.85	-0.45	0.72	-0.30	-0.07	-0.09	-0.33	-0.37	1.62	-0.16
Communications	22	14	-0.16	0.70	0.19	-0.72	-0.28	-0.37	-0.07	0.42	0.02	-0.52	0.06	-0.36
Other social science	23	21	-0.43	-0.52	0.90	-0.43	1.47	-0.37	-0.15	-0.20	-0.38	-0.44	1.40	-0.18
Social work	24	28	-1.54	-0.67	2.58	-0.70	0.75	-0.52	-0.47	-0.66	-0.56	-0.56	0.33	-0.36
Nursing	25	27	-1.71	0.03	0.06	0.26	-0.79	-0.66	-0.66	-0.86	-0.54	-0.07	-1.02	-0.46
Family and consumer science	26	26	-1.85	0.26	0.37	-0.52	0.19	-0.24	-0.53	-0.67	0.04	-0.36	-0.40	0.60
Education	27	29	-1.21	1.76	-0.78	-1.18	-0.89	-0.15	-0.48	-0.47	-0.53	-0.44	-0.57	4.82
Protective services	28	13	0.66	-0.47	1.97	-1.17	2.02	-0.44	-0.60	-0.60	-0.31	-0.59	0.09	-0.48
Fitness and nutrition	29	18.5	0.24	1.08	0.17	-0.90	-0.80	-0.26	-0.58	-0.80	-0.20	0.36	-0.69	0.22

Note: All measures except the SAT math and grading ranks are given in standard deviations. The course measures are the average number of courses taken by graduates in each major, as measured in the Baccalaureate and Beyond. SAT math rank is the major's rank in average SAT math scores, also from the Baccalaureate and Beyond. Grading rank is the major's rank in grading standards, calculated as the difference between the major's SAT composite score rank and its average GPA rank, from the Baccalaureate and Beyond. The gender and racial percentages are calculated from the American Community Survey 2009-2014, using graduates from 2003 to 2008.

Table A1 shows that some of our measures are correlated. Majors that have high-achieving students tend to also have high grading standards, more males, and more Asian students. More female-heavy majors tend to have more white students and be less competitive (by the variables that proxy for competitiveness). The black and Hispanic shares of a major are also positively correlated.

By characterizing majors as vectors of characteristics, we can calculate the "distance" and "direction" of major switches. We calculate the academic distance (distance in the x component) between majors m and $\tilde{m}$ as

$$D(m^x, \tilde{m}^x) = 1 - \frac{m^x \cdot \tilde{m}^x}{||m^x||||\tilde{m}^x||}$$

This is the "angular distance" between the two vectors, equaling one minus the cosine of the angle between the two vectors. The distance varies between 0 and 1 and equals 0 if the vectors point in the same direction.[31] The angular distance has been used previously by Gathmann and Schoenberg (2010) to measure the distance between occupations, but we are the first to use it to study the distance between majors.[32]

To give a few examples of the size of major switches, engineering to education is one of the largest switches, 2.25 standard deviations above the average switch. History to earth sciences is about 1 standard deviation above the mean. Art history to economics is almost at the average (0.02 standard deviations above), while art history to nursing is 1 standard deviation below the average size. Some of the smallest switches are within-STEM switches, such as from engineering to biological sciences (1.4 standard deviations below average).[33]

We use the angular distance between m^x and $\tilde{m}^x$ instead of the more familiar Euclidean distance, because Euclidean distance captures both changes in angle (i.e., if one switches from a major with more science than humanities to a major with more humanities than science) and changes in magnitude (i.e., if one switches to a major with more overall course requirements). We wish to measure those two things

[31] Goldhaber, Cowan, Long and Huntington-Klein (2015) also construct a measure of the distance between academic departments, based on the overlap in courses taken by students in each department, to study the dispersion of courses that students take.

[32] We convert distance to standard deviations, using the whole distribution of potential major switches (each major to each other major) rather than just the observed switches in the data.

[33] One can look at Table 2 to see how these majors differ in course requirements.

separately, calling the former distance and the latter direction. The angular distance better captures our notion that the cost of switching is related to the degree of course overlap in the two majors.

We can also measure the "direction" of major switches, both in the course (x) and non-course (θ) components. If one switches from major m to major $\tilde{m}$, then the direction of switch in element j is

$$d_j(m_j^k, \tilde{m}_j^k) = \tilde{m}_j^k - m_j^k.$$

where $k = x, \theta$. If a student changes from a major that is one standard deviation above the mean in math requirements to one that is 1.5 standard deviations above the mean, the direction of change in the math component is +0.5. We do not use the absolute value to measure direction, because the sign of the change tells us something important. We define direction similarly for each θ characteristic. The direction of a switch is therefore a set of measures, one for each element of the major vector, rather than a single composite measure.

4 Major Switching: Results

4.1 Descriptive Statistics

Table 3 reports some switching patterns from our data. First, we report the majors with the highest switch-out rates, overall and by gender.[34] Business and economics both have low switch-out rates, as does engineering, surprisingly. Some gender differences stand out. Men leave education at high rates (49%), while women leave at low rates (32%). Women also leave computer science at much higher rates than men do (62% vs. 37%).

Next, we list the most common switches observed in our data. Note that both business to education and education to business are among the most common moves students make. While this may seem contradictory, such a pattern is consistent with our model. Students have different preferences over majors and learn about their abilities and major characteristics, leading to switching in opposite directions like this.

[34]We restrict here to majors with at least 25 starting students.

Table 3
Major Switching: Descriptive analysis

Majors with highest switch-out rates

Overall	Men	Women
General science (76%)	Earth/physical science (74%)	General science (78%)
Earth/physical science (74%)	Med/health services (67%)	Earth/physical science (74%)
Med/health services (65%)	Other social science (53%)	Med/health services (64%)
Biology (52%)	Education (49%)	Computer science (62%)
Computer science (43%)	Philosophy/religion (44%)	Biology (57%)

Majors with lowest switch-out rates

Overall	Men	Women
Business (19%)	English (15%)	Business (18%)
History (27%)	Economics (16%)	Other social science (27%)
Economics (29%)	History (18%)	Engineering (27%)
English (31%)	Business (22%)	Public admin/law (31%)
Engineering (31%)	Psychology (31%)	Education (32%)

Most common switches

Overall	Men	Women
Comp. sci. to business	Comp. sci. to business	Education to psychology
Education to business	Engineering to business	Psychology to other soc. sci.
Business to education	Education to business	Education to business

Majors with largest net gains and losses from switching

Largest net gains	Largest net losses
Business	Biology
Other social science	Computer science
Economics	Med/health services
Philosophy/religion	Engineering
Mathematics	Earth/physical science

Note: For majors with the highest and lowest switch-out rates, we restrict to majors with at least 25 students beginning in those majors. For the male and female columns, we also require 10 students of that gender starting in the major. Net gains from switching are calculated as total in-switchers minus out-switchers.

As majors differ in size, we also look at the majors with the highest and lowest *net* switching, defined as the "in-switchers" minus "out-switchers". This is how many students the major gains in our data through the switching process. The net losers are dominated by STEM fields, including biology and computer science, while net gainers are mostly business and social sciences. Engineering, despite a relatively low switch-out rate, loses students because of an even lower switch-in rate.[35]

[35]Only 17 percent of engineering graduates are in-switchers, lowest of any major in our data.

4.2 Probability of Switching

We first explore the determinants of major switching. The determinants we investigate include those suggested by the model (e.g., GPA) and others that are of descriptive interest (e.g., race, gender, and cognitive ability). We run linear probability models of the form

$$switch_{im} = \Psi_i\beta_1 + \Phi_m\beta_2 + \beta_3 GPA_i + \epsilon_i$$

where i is the student and m is the major the student's first major choice.[36] The dependent variable is an indicator for leaving that major. Ψ_i includes personal characteristics like race and gender, Φ_m includes characteristics of the first major, and GPA_i is the student's early-college GPA.

Table 4 reports results of these regressions. As predicted by the model, lower grades predict switching majors; a one-point lower GPA (on a 4-point scale) is associated with a 7.6 percentage point higher probability of switching. Women are about 6 percentage points more likely to switch than men, but we have shown in another paper that this is because men are more likely to drop out than women are (Astorne-Figari and Speer 2018). The gender switching gap among graduates in Table 4 reflects women's higher likelihood of "trying something else" rather than leaving school, and does not imply that women are more likely to be mismatched with their major or more sensitive to mismatch.[37]

Column 2 suggests that females may be more sensitive to low grades in the switching decision than males are, but the coefficient on the interaction term is not significant.[38] In results we do not include here, we find no significant interaction of AFQT score and GPA, and thus no evidence that lower-ability students respond less to low grades because they "expect" to get low grades.

[36] We have also run probit models for all regressions with a dummy variable as the dependent variable. Results are nearly identical to those we report.

[37] One might suspect that higher rates of switching for minorities reflect a lack of familiarity with college relative to whites, but the racial gaps are of similar size when restricting to students whose parents do not have degrees.

[38] A gender difference in sensitivity to grades would be consistent with evidence from Ost (2010) and Owen (2010), although Kugler et al. (2017) and Astorne-Figari and Speer (2018) find mixed evidence on this point.

Table 4
Major Switching: Personal and First Major Characteristics

	Dependent Variable: Switch Majors				
	(1)	(2)	(3)	(4)	(5)
Personal Characteristics:					
Female	0.060**	0.059**	0.047*	0.070***	0.067***
	(0.024)	(0.024)	(0.026)	(0.025)	(0.025)
Early GPA	-0.076***	-0.039	-0.078***	-0.078***	-0.076***
	(0.025)	(0.037)	(0.025)	(0.025)	(0.025)
Female*Early GPA		-0.069			
		(0.050)			
Black	0.062*	0.061*	0.059*	0.056	0.053
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Hispanic	0.070*	0.069*	0.071*	0.066*	0.064*
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Asian	-0.054	-0.053	-0.051	-0.061	-0.061
	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
AFQT	-0.007	-0.019	-0.014	-0.011	-0.016
	(0.013)	(0.019)	(0.014)	(0.013)	(0.014)
Female*AFQT		0.023			
		(0.025)			
First Major Characteristics:					
Grading std			0.010		
			(0.028)		
Avg SAT Math			0.022		
			(0.026)		
Male pct			-0.081***		
			(0.023)		
Black pct			-0.016		
			(0.019)		
Hispanic pct			-0.018		
			(0.021)		
Asian pct			0.060***		
			(0.022)		
Competitiveness				0.024	0.026*
				(0.015)	(0.015)
AFQT*Competitiveness					-0.033**
					(0.015)
Early GPA*Competitiveness					0.020
					(0.027)
Constant	0.322***	0.325***	0.331***	0.319***	0.326***
	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)
Observations	1,662	1,662	1,662	1,662	1,662
R-squared	0.017	0.019	0.032	0.019	0.022

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: The sample includes all students who graduated from a four-year college. The dependent variable is a dummy for switching majors. Early GPA is average GPA in the first two years of college. GPA is de-meaned so that the main effect is the effect at the mean GPA. The AFQT score is in standard deviations. Average SAT math is the average SAT math score in the major, from the Baccalaureate and Beyond. Grading standards are calculated as the difference between the major's SAT total score rank and its average GPA rank, from the Baccalaureate and Beyond. The gender and race percentages are the makeup of the major as calculated in the ACS, in standard deviations. Competitiveness is the average of Asian percentage, grading standards, and average SAT math.

Columns 3-5 add characteristics of the student's first major – grading standards, the average SAT math score in the major, and the male, black, Hispanic, and Asian percentages of the major. When all characteristics are included (column 3), the Asian share has the largest positive effect on switching. High average SAT math scores and high grading standards have no significant effect here.

Because several of these variables – particularly the Asian share, grading standards, and SAT math scores – are positively correlated and could all be proxying for competitiveness, it is useful to combine them into a single variable. We construct a "competitiveness index" equal to the average of these three major-level measures.[39] In columns 4 and 5, we see that this variable positively predicts switching, but only for lower-AFQT students. Students who come in with higher cognitive ability are undeterred by competitive majors.

To look specifically at how the determinants of switching differ for males and females, we include Table 5. Columns 1-3 include females only, while columns 4-6 include males only. While the effect of grades does not significantly differ by gender (see Table 3), we do see that the point estimates on GPA are much larger for females and insignificant for men.

The other striking result here is the difference in the effect of the competitiveness variable. Women are more likely to leave more competitive majors, but we see no such effect for men. In column 3, the entire effect of competitiveness on major switching is being driven by lower-AFQT women. Higher-ability women and men of all abilities are not deterred by competitive majors, but lower-ability women are. In fact, if anything, lower-ability men are *less* deterred by competitive majors than higher-ability men are. It is not surprising that lower-ability students would leave competitive majors at higher rates, but it is surprising that this is only true for women.

In interpreting this result, it is not likely that many students prefer difficult, competitive majors, all else being equal. Rather, competitiveness is likely correlated with things students do like, such as earnings or prestige.[40] What our results suggest is

[39]While there is evidence that men are more competitive than women on average (Niederle and Vesterlund 2011), we are not aware of such evidence for Asian students, although some stereotypes might imply such a relationship. We note only that Asian share is correlated with the other variables and do not claim that majors are competitive *because* they have many Asian students.

[40]In fact, the competitiveness component variables are all positively correlated with a major's average earnings.

Table 5
Major Switching by Gender

	Women			Men		
	(1) Switch	(2) Switch	(3) Switch	(4) Switch	(5) Switch	(6) Switch
Personal Characteristics:						
Early GPA	-0.111***	-0.113***	-0.099***	-0.034	-0.034	-0.031
	(0.034)	(0.034)	(0.035)	(0.037)	(0.037)	(0.038)
Black	0.038	0.027	0.023	0.068	0.087	0.089
	(0.045)	(0.045)	(0.045)	(0.060)	(0.059)	(0.059)
Hispanic	0.066	0.058	0.054	0.070	0.070	0.074
	(0.050)	(0.050)	(0.050)	(0.059)	(0.059)	(0.059)
Asian	-0.046	-0.054	-0.055	-0.056	-0.068	-0.067
	(0.084)	(0.084)	(0.084)	(0.086)	(0.086)	(0.086)
AFQT	-0.008	-0.006	-0.029	-0.015	-0.012	-0.013
	(0.018)	(0.018)	(0.019)	(0.021)	(0.020)	(0.020)
Major Characteristics:						
Grading std	0.005			-0.019		
	(0.037)			(0.043)		
Avg SAT Math	0.039			-0.010		
	(0.035)			(0.040)		
Male pct	-0.070**			-0.083**		
	(0.029)			(0.040)		
Black pct	-0.028			-0.020		
	(0.026)			(0.029)		
Hispanic pct	-0.007			-0.021		
	(0.027)			(0.033)		
Asian pct	0.081***			0.062*		
	(0.031)			(0.035)		
Competitiveness		0.063***	0.058***		-0.022	-0.027
		(0.020)	(0.020)		(0.022)	(0.022)
AFQT*Competitiveness			-0.077***			0.030
			(0.021)			(0.021)
Early GPA*Competitiveness			0.031			-0.019
			(0.041)			(0.039)
Constant	0.393***	0.406***	0.412***	0.341***	0.325***	0.320***
	(0.022)	(0.020)	(0.020)	(0.025)	(0.022)	(0.023)
Observations	970	970	970	692	692	692
R-squared	0.042	0.027	0.040	0.029	0.014	0.017

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: The sample includes all students who graduated from a four-year college. The first three columns are only women, while the next three columns are only men. The dependent variable is a dummy for switching majors. Early GPA is average GPA in the first two years of college. "High AFQT" is a dummy for being in the top half of the AFQT distribution. Average SAT math is the average SAT math score in the major, from the Baccalaureate and Beyond. Grading standards are calculated as the difference between the major's SAT total score rank and its average GPA rank, from the Baccalaureate and Beyond. The gender and race percentages are the makeup of the major as calculated in the ACS, in standard deviations. Competitiveness is the average of Asian percentage, grading standards, and average SAT math.

that men dislike the competition less than women do. Our finding is consistent with men (especially lower-ability men) being more overconfident than women, as suggested by Niederle and Vesterlund (2011). It is not clear if men or women are making the "wrong" decision by leaving more competitive majors. It may be that lower-ability women are responding rationally to the difficult environment and realizing that they will not succeed in the major, while lower-ability men are being foolish by staying. On the other hand, it may be that men are better able to "put up" with an unpleasant experience in exchange for high returns. Our results do not prove either interpretation, but the gender difference we document is striking.

To summarize the results of this section, grades are strong predictors of major switching: one point lower early-college GPA leads to a 7-8 percentage point higher switching rate, with a larger effect for women than for men. Competitiveness of a major predicts switching out, but only for lower-ability females. Males and higher-ability females are undeterred by competitive majors.

4.3 Distance of Switching and Grade Improvement

Now we examine the determinants of the academic distance of switching, and in particular the relationship of this distance with grades, which signal the quality of the course match. Recall that our distance measure is the angular distance defined in Section 3. The model predicts that low grades should lead to larger switches, and also that larger switches should lead to larger grade improvements. We now run regressions – restricting to major switchers – of the form

$$D_i(m^x, \tilde{m}^x) = \Psi_i \lambda_1 + \Phi_m \lambda_2 + \lambda_3 GPA_i + \upsilon_i$$

where the dependent variable is the distance of switch from major m to major $\tilde{m}$ (defined in Section 3) and Ψ_i, Φ_m, and GPA_i are the same as in the previous tables.

Table 6, Panel A has the results.[41] As expected, grades have a large impact on the distance of major switches. Students with lower grades make larger switches. A one point lower GPA is associated with about a 0.27 standard deviation larger switch. We find only an insignificant gender difference in how distance of switch responds to grades.

[41] Here, as in some future tables, we restrict to switchers. When comparing men who switch to women who switch, the latent distributions of switchers are different. In Table 4, we showed that women are more likely to switch majors than men are. Thus, selection into the switching sample is different for men and women. Table 4 represents the extensive margin of switching, while these tables that use only switchers represent the intensive margin.

Table 6
Academic Distance of Switching

	Dependent variable: Distance of switch							
	Panel A: All switchers				Panel B: STEM Leavers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.105	-0.096	-0.085	-0.072	0.108	0.122	0.130	0.182
	(0.075)	(0.076)	(0.076)	(0.077)	(0.169)	(0.175)	(0.129)	(0.166)
Early GPA	-0.266***	-0.344***	-0.275***	-0.271***	-0.263	-0.308	-0.241*	-0.271*
	(0.075)	(0.116)	(0.075)	(0.075)	(0.160)	(0.233)	(0.122)	(0.154)
Female*Early GPA		0.141				0.062		
		(0.147)				(0.326)		
Black	-0.077	-0.069	-0.099	-0.095	-0.232	-0.245	-0.272	-0.273
	(0.104)	(0.105)	(0.104)	(0.104)	(0.227)	(0.230)	(0.174)	(0.220)
Hispanic	0.030	0.036	0.007	0.004	-0.076	-0.082	-0.086	-0.106
	(0.111)	(0.112)	(0.113)	(0.112)	(0.224)	(0.228)	(0.171)	(0.216)
Asian	-0.174	-0.185	-0.211	-0.206	-0.109	-0.093	-0.202	-0.274
	(0.206)	(0.206)	(0.207)	(0.207)	(0.372)	(0.377)	(0.285)	(0.363)
AFQT	0.105**	0.100**	0.092**	0.097**	0.274***	0.291***	0.109	0.409***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.094)	(0.101)	(0.074)	(0.146)
AFQT*Early GPA		-0.065				0.094		
		(0.078)				(0.198)		
Avg SAT Math			-0.002				-0.211*	
			(0.061)				(0.110)	
Grading std			0.082				1.060***	
			(0.068)				(0.128)	
Competitiveness				0.084*				0.387***
				(0.045)				(0.125)
AFQT*Competitiveness				0.038				-0.175
				(0.044)				(0.131)
Constant	0.092	0.093	0.104	0.078	0.452***	0.436***	0.133	0.116
	(0.065)	(0.066)	(0.066)	(0.066)	(0.146)	(0.152)	(0.129)	(0.184)
Observations	618	618	618	618	141	141	141	141
R-squared	0.033	0.036	0.039	0.039	0.098	0.100	0.481	0.176

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: The sample in columns 1-4 is all graduates who switched majors. The sample in columns 5-8 is all students who switched out of STEM. The dependent variable is the distance of major switch, calculated as described in Section 3. Early GPA is average GPA in the first two years of college. GPA is de-meaned so that the main effect is the effect at the mean GPA. "High AFQT" is a dummy for being in the top half of the AFQT distribution. Average SAT math is the average SAT math score in the major, from the Baccalaureate and Beyond. Grading standards are calculated as the difference between the major's SAT total score rank and its average GPA rank, from the Baccalaureate and Beyond. The gender and race percentages are the makeup of the major as calculated in the ACS, in standard deviations. Competitiveness is the average of Asian percentage, grading standards, and average SAT math.

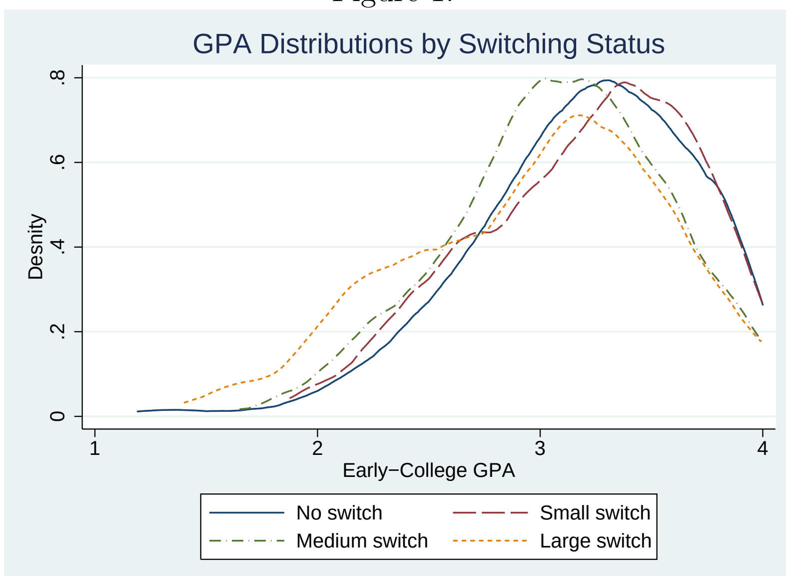
Columns 3 and 4 include some major characteristics, with only a suggestive result that highly competitive majors drive students to make larger changes. Grades seem to be the main driving factor in the distance of switching.[42]

Figure 1 shows the distribution of early-college GPA for those who do not switch

[42] All of our distance results are robust to using an alternative binary measure of distance, which takes a value of 1 if the new major's dominant field of course content is different from that of the old major. These results are available upon request.

majors (solid line) and then for switchers, broken up into three terciles by the size of the switch. The non-switchers and small switchers have similar GPAs, higher than the other groups. The small switchers are likely those who were mismatched mostly on preferences rather than academics. The medium switchers have lower GPAs than those two groups, and the lowest GPAs of all belong to the large switchers.

Figure 1:



If major switches are to correct academic mismatch, then grades should improve when students switch majors, and should improve more when students make larger switches. Table 7 investigates this. Here we regress

$$\Delta GPA_i = \Psi_i \gamma_1 + \Phi_m \gamma_2 + \gamma_3 switch_{im} + \gamma_4 D_i(m^x, \tilde{m}^x) + \alpha_i$$

The dependent variable is the change in GPA from the first two years of college to the last two years.[43] Surprisingly, there is no evidence that switching majors improves grades. While column 2 shows that larger switches are associated with larger grade improvement, column 3 shows us that this is only because of mean reversion in grades. Students with low early grades see some bounce-back relative to other students, whether they switch majors or not. This casts doubt on our interpretation of switching as a way to improve the academic match. One possible explanation is that students learn about

[43]Results are similar for every definition of early and late GPA that we have tried.

Table 7
Change in GPA with Major Switches

	Dependent variable: Change in GPA					
	Panel A: All students/switchers			Panel B: STEM starters/leavers		
	(1)	(2)	(3)	(4)	(5)	(6)
Major switch	-0.005					
	(0.018)					
Switch out of STEM				0.032		
				(0.042)		
x distance of switch		0.060***	0.015		0.040	0.001
		(0.020)	(0.016)		(0.041)	(0.035)
Early GPA	-0.520***		-0.548***	-0.500***		-0.493***
	(0.018)		(0.030)	(0.040)		(0.064)
Female	0.079***	0.073*	0.103***	0.067*	0.051	0.092
	(0.018)	(0.038)	(0.031)	(0.040)	(0.081)	(0.066)
Black	-0.139***	-0.006	-0.093**	-0.108*	0.139	-0.011
	(0.027)	(0.052)	(0.042)	(0.059)	(0.107)	(0.090)
Hispanic	-0.073***	-0.103*	-0.059	-0.168***	-0.083	-0.069
	(0.028)	(0.056)	(0.045)	(0.062)	(0.107)	(0.087)
Asian	-0.070	0.016	0.017	-0.130	0.010	0.023
	(0.045)	(0.103)	(0.082)	(0.086)	(0.175)	(0.143)
AFQT	0.053***	-0.013	0.063***	0.018	-0.037	0.023
	(0.010)	(0.020)	(0.017)	(0.023)	(0.045)	(0.038)
Change in competitiveness			-0.013			-0.017
			(0.014)			(0.040)
Constant	0.100***	0.099***	0.065**	0.112***	0.133*	0.072
	(0.016)	(0.033)	(0.027)	(0.034)	(0.075)	(0.078)
Observations	1,603	599	599	403	135	135
R-squared	0.350	0.024	0.383	0.328	0.046	0.375

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: The sample in columns 1-3 is all graduates or all switchers. The sample in columns 4-6 is all graduates who started in STEM or switched out of STEM. The dependent variable is late GPA minus early GPA. Early GPA is average GPA in the first two years of college, and late GPA is average GPA in the last two years of college. "High AFQT" is a dummy for being in the top half of the AFQT distribution. SAT Math change is the change in the average SAT math score of the major from first major to last major. The gender and race percentages are the makeup of the major as calculated in the ACS, in standard deviations. Competitiveness is the average of Asian percentage, grading standards, and average SAT math.

their ability in the first major, but not generally about their ability in all majors, so their new major choice is not necessarily any better for them.

Also surprisingly, in column 3, the change in competitiveness is not related to grade improvement. Moving to an "easier" major does not seem to help grades. It could be that students compensate for an easier major with lower work effort to keep grades constant. This finding also seems to rule out another story: that high-performing students move to more difficult majors and then receive lower grades, which could have explained the zero on major switching.[44]

[44]The results of Table 7 are similar if we exclude switchers who had near-perfect early GPAs (and

To summarize, we find strong evidence that the lower a student's grades, the larger a major switch she will make. However, these switches do not seem to improve the students' grades. We also find no evidence that moving to easier or harder majors affects grades. So the evidence on switches as a way to improve the academic match is mixed. This may suggest that major switches are more driven by non-course preferences than by academic match. We explore this idea next.

4.4 Direction of Switching

Next, we look at the direction of major switching. The model tells us that students who switch majors should be moving toward better matches, both in the academic and preference dimensions. First, we look at how the non-course characteristics of the major (m^θ) change with major switches. Because we cannot observe students' preferences, the best we can do is a descriptive analysis on the prevailing patterns of switching to learn something about those preferences. Here our regressions – restricting to those who switched majors – are of the form

$$d_{ij}(m^k, \tilde{m}^k) = \Psi_i \xi_1 + \xi_2 m_j^k + \xi_3 GPA_i + \nu_i$$

for $k = x, \theta$. The term d_{ij} is the direction of switch of student i in characteristic j (e.g., math courses, gender makeup) when switching from major m to major $\tilde{m}$, as defined in Section 3. The term m_j^k is the initial major's value of characteristic j.

We first focus on the direction of switches in non-course characteristics. Table 8 gives the results, which are striking.[45] When students switch majors, they move to majors that "look like them": females to female-heavy majors, whites to white-heavy majors, blacks to black-heavy majors, and so on. The effect is strongest for women moving to far less male-dominant majors.[46]

There are two potential stories here, which we cannot distinguish. One says that

thus could not see any grade improvement).

[45]Note that students are moving away from their first major choice in every characteristic. This suggests that most switching students are leaving majors with more "extreme" characteristics rather than more average majors.

[46]The gender makeup of the major is likely correlated with the gender makeup of the faculty in that major, which we do not observe. Most research finds this to be only a minor influence on major choice (Hoffmann and Oreopoulos (2009), Price (2010), Kugler et al. (2017)).

Table 8
Direction of Switching (Non-Course Characteristics)

	Dependent Variables: Change in Major Characteristic From Old to New Major							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Avg SAT M	Grading	Male pct	White pct	Black pct	Hisp pct	Asian pct	Competitiveness
Female	-0.505***	-0.467***	-0.538***	0.252***	0.194**	0.158*	-0.354***	-0.442***
	(0.077)	(0.068)	(0.081)	(0.078)	(0.087)	(0.091)	(0.074)	(0.063)
Black	0.127	-0.031	-0.040	-0.174*	0.216*	0.196	0.044	0.047
	(0.104)	(0.091)	(0.104)	(0.104)	(0.118)	(0.122)	(0.098)	(0.084)
Hispanic	0.011	-0.058	0.013	-0.197*	0.206	0.266**	0.045	-0.005
	(0.113)	(0.099)	(0.113)	(0.113)	(0.127)	(0.132)	(0.106)	(0.092)
Asian	0.463**	0.370**	0.319	-0.245	-0.070	-0.157	0.289	0.374**
	(0.211)	(0.185)	(0.212)	(0.212)	(0.238)	(0.248)	(0.200)	(0.171)
High AFQT	0.205**	0.173**	0.098	0.010	-0.143	0.082	0.011	0.129**
	(0.081)	(0.071)	(0.081)	(0.080)	(0.091)	(0.095)	(0.076)	(0.065)
Early GPA	0.158**	0.043	0.032	-0.064	-0.132	-0.128	0.142**	0.114*
	(0.076)	(0.067)	(0.076)	(0.076)	(0.086)	(0.090)	(0.072)	(0.062)
First major's value of dependent variable	-1.028***	-0.946***	-0.979***	-1.009***	-0.954***	-0.946***	-0.958***	-0.974***
	(0.039)	(0.038)	(0.040)	(0.038)	(0.044)	(0.042)	(0.036)	(0.037)
Constant	0.136	-0.070	0.185**	-0.072	-0.074	-0.140	0.133	0.065
	(0.085)	(0.075)	(0.086)	(0.085)	(0.096)	(0.100)	(0.081)	(0.069)
Observations	618	618	618	618	618	618	618	618
R-squared	0.538	0.512	0.504	0.538	0.436	0.454	0.544	0.540

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: The sample is all major switchers. The dependent variables are the change in each major characteristic, all measured in standard deviations. Early GPA is average GPA in the first two years of college. "High AFQT" is a dummy for being in the top half of the AFQT distribution. Average SAT math is the average SAT math score in the major, from the Baccalaureate and Beyond. Grading standards are calculated as the difference between the major's SAT total score rank and its average GPA rank, from the Baccalaureate and Beyond. The gender and race percentages are the makeup of the major as calculated in the ACS, in standard deviations. Competitiveness is the average of Asian percentage, grading standards, and average SAT math.

through major switching, students find their preferred peer group or identity, not just their best academic match. If that is true, then it would appear that students prefer a peer group that is similar to them.[47] In this story, women switch to female-heavy majors *because* they are female-heavy. The second story says that those with similar observable characteristics have similar preferences and thus end up in the same types of majors. Women end up in female-heavy majors because they have preferences similar to other women, not specifically because they prefer to be around other women. If the second story is true, one is still left to wonder why some women find these majors immediately, while others find them only after switching. Either way, these results in Table 8 are striking, but we cannot nail down the mechanisms behind them.[48]

[47]See Akerlof and Kranton (2000) for a discussion of how identity can affect agents' economic behavior.

[48]Recall that the sample here is only switchers. If non-switchers are included, the coefficient on

We see in the top row of coefficients that women who switch majors – when compared with men who switch majors – move to less competitive, lower-SAT, less Asian, less male, easier-grading majors. As these characteristics are highly correlated, it is unsurprising that they move together. The largest point estimates are for the male percentage and SAT math scores. Not only are women leaving competitive majors (Table 5), but when they leave, they are likely to choose a new major that is far less competitive. This suggests again that women's preferences s^θ include a stronger distaste for competitive environments than men's preferences do.

These results highlight an advantage of our approach in studying major switches specifically. A standard major choice analysis would reveal that women are in less competitive majors, but we are showing that some of this sorting does not occur until the switching decision. This suggests that women learn some about these preferences during college.

Next, we look at how the course requirements of majors (m^x) change with major switches. The model implies that if a student receives poor grades in a subject, she should move to a major that requires less of that subject. Unfortunately, our grade measures are not course-specific. However, we do know the characteristics of the first major, so we can guess that if the first major was heavy in math and light in humanities, for example, the grade feedback the student got was more informative about math than about humanities. This limitation in our data is likely to attenuate the results here.

In Table 9, we run regressions similar to Table 8, but for the direction of change in course content when a student switches from major m to major $\tilde{m}$. We interact GPA with the course characteristic of the initial major, expecting that the GPA interaction terms will be positive, meaning GPA has a larger effect the more of that subject the initial major required.

The coefficients on the interaction terms are indeed all positive, though only some (science/engineering, business, and social sciences) are significant. This is evidence that receiving higher grades in a certain course area makes the student move toward fields that emphasize that area more highly.

There are also a few gender differences in the switching patterns. Women who

female in the "Male percentage" regression is -0.253, instead of the -0.538 we report, because more than half of the observations (the non-switchers) have a zero dependent variable.

Table 9
Direction of Switching (Course Characteristics)

	Dependent Variables: Change in Major Characteristic From Old to New Major						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Math	Humanities	For Lang	Sci/Engin	Edu	Business	Soc Sci
Female	-0.180**	-0.077	-0.039	-0.146**	0.330***	-0.170**	-0.089
	(0.081)	(0.087)	(0.102)	(0.073)	(0.079)	(0.074)	(0.087)
Black	0.070	0.108	0.104	-0.162	-0.140	-0.041	0.207*
	(0.107)	(0.117)	(0.136)	(0.099)	(0.107)	(0.099)	(0.117)
Hispanic	-0.007	-0.048	-0.058	-0.015	-0.068	-0.073	0.134
	(0.116)	(0.126)	(0.147)	(0.107)	(0.115)	(0.106)	(0.127)
Asian	-0.014	-0.171	-0.009	0.061	-0.373*	0.141	0.341
	(0.217)	(0.236)	(0.276)	(0.200)	(0.217)	(0.200)	(0.238)
High AFQT	-0.019	0.152*	0.281***	0.045	-0.158*	-0.037	0.105
	(0.083)	(0.091)	(0.106)	(0.076)	(0.083)	(0.076)	(0.091)
Early GPA	0.201**	0.128	0.057	0.114	0.052	-0.208***	-0.034
	(0.078)	(0.086)	(0.100)	(0.073)	(0.079)	(0.075)	(0.086)
First major's value of	-0.819***	-0.865***	-0.941***	-0.864***	-1.062***	-1.081***	-0.915***
dependent variable	(0.045)	(0.046)	(0.055)	(0.034)	(0.044)	(0.047)	(0.042)
Early GPA*First value	0.075	0.103	0.015	0.159**	0.020	0.189***	0.190**
	(0.090)	(0.092)	(0.098)	(0.064)	(0.075)	(0.087)	(0.079)
Constant	0.057	0.033	-0.003	0.050	-0.059	-0.038	0.043
	(0.088)	(0.096)	(0.113)	(0.081)	(0.088)	(0.081)	(0.097)
Observations	618	618	618	618	618	618	618
R-squared	0.368	0.391	0.391	0.524	0.543	0.503	0.460

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Note: The sample is all major switchers. The dependent variables are the changes in major course content, all measured in standard deviations. Course content is the average number of courses in each field taken by a graduate in that major. Early GPA is average GPA in the first two years of college. GPA is de-meaned so that the main effect is the effect at the mean GPA. "High AFQT" is a dummy for being in the top half of the AFQT distribution.

switch majors, when compared with men who switch, seek out majors with less math, science, and business content, and more education content.

To summarize our main results, grades, gender, and major characteristics are all important for understanding major switching behavior. Low grades lead to major switches – and the lower the grades, the larger the switch. However, surprisingly, switching majors does not improve students' grades. When students change majors, they seek out majors that match their own characteristics in terms of race and gender makeup. The competitiveness of the major is related to switching behavior, and this is driven entirely by its effect on lower-ability females.

One thing left out of our model for simplicity is a major's earnings return. One might imagine that instead of majors differing in many dimensions, as in our model, they are ranked by something like average earnings. Earnings are not completely absent from our analysis, as the academic match between student and major is likely related to the student's future earnings (Guvenen et al. 2015). Furthermore, several of our major characteristics (e.g., average SAT math) are correlated with average earnings. Students who show a "preference" for these characteristics may be actually showing a preference for high earnings. Several other papers have found that giving information about major earnings does not induce many students to switch majors, while preference factors dominate (e.g., Wiswall and Zafar 2015). In our results, there is no discernible movement toward higher-paying majors; 51% of major switches in our data are to majors with lower average earnings, while 49% are to higher earning majors. The switching patterns also show that students move away from high-SAT and competitive majors, which tend to be the high-earning majors.

5 Switching Out of STEM: Results

For our last set of results, we focus particularly on students switching out of STEM fields.[49] While STEM majors do not appear explicitly in the model, they occupy a particular range in both the course (high science and math) and non-course (competitive, male and Asian shares) components. STEM fields are typically high-paying and are considered important for the nation's economic growth, yet tend to have high net switch-out rates, especially among women (Stinebrickner and Stinebrickner 2013, Astorne-Figari and Speer 2018).

In our data, 33% of males and 19% of females start in STEM majors. Among these STEM starters, 30% of males and 43% of females switch out of STEM.[50] Because STEM fields have particular characteristics in both the x and θ components, the key question is why women are more likely to leave. Is it because of the course content, because of the men, because of the competitiveness, or something else? We try to provide answers by looking at the determinants of leaving and where students go when

[49]While there are students who switch *into* STEM fields – about 10% of the non-STEM-starters – most of these are students who add a STEM second major to their first major. It is difficult to conceptualize the concepts of distance and direction for adding a second major, and this requires a different type of model. We leave this for future research.

[50]Despite males being only 42% of the college graduate sample, they make up 55% of the students who start in STEM fields. Females, who are only 45% of STEM starters, make up 54% of the out-switchers.

they leave STEM.

First, Table 10 investigates the determinants of switching out of STEM.[51] Here the gender gap (about 15 percentage points) is more than twice as large as the overall gender switching gap (6 percentage points, from Table 3). While we emphasized in the overall results that a gender differential in switching rates was offset by an opposite gap in dropout rates, the same is not true for STEM. We find in Astorne-Figari and Speer (2018) that the gender gap in switching out of STEM is much larger than any corresponding gap in dropping out of college. Even including dropouts, women are far less likely to persist in a STEM field than men are.

Low grades are also a strong predictor of leaving STEM. A one point lower GPA is associated with an 17-19 percentage point increase in switching out of STEM. The overall effect in Table 3 was only about 7 percentage points. None of the large gender gap in switching is explained by grades, and we find only suggestive evidence for STEM that women are more sensitive to low grades.[52] Oddly, within STEM fields (which all rank high on competitiveness), the more competitive majors actually have lower switch-out probabilities.

Next, we look at the academic distance moved by those who switch out of STEM (Table 6, Panel B). As in the overall results, lower grades lead to larger switches away from STEM. Once again, though, these large switches do not seem to improve students' grades (Table 7, Panel B). The main driver of grade improvement seems to be mean reversion rather than switching.

Table A2 shows the destinations of students who switch out of STEM separately by gender, with majors sorted by their academic distance to STEM fields. Students who switch to academically "close" majors like nursing and medical/health services are overwhelmingly female. These are both similar to STEM in course content but very different in characteristics like gender makeup.[53] On the other hand, most STEM

[51]The dependent variable here is equal to one if the student started in STEM and finished out of STEM. If a student switched from one STEM field to another, the dependent variable is equal to zero.

[52]Although our sample is not large enough to find significant differences across college types, we have compared these results for mostly-male colleges and mostly-female colleges. If anything, the gender gap in leaving STEM is largest at mostly-female colleges. However, we also note that students who select into colleges that are gender-imbalanced are likely different from students at more balanced colleges.

[53]Nursing and medical/health services are 90% and 60% female, respectively.

Table 10
Switching out of STEM: Personal and First Major Characteristics

	Dependent Variable: Switch out of STEM				
	(1)	(2)	(3)	(4)	(5)
Personal Characteristics:					
Female	0.121***	0.148***	0.058	0.072	0.072
	(0.047)	(0.047)	(0.051)	(0.046)	(0.046)
Early GPA	-0.191***	-0.160***	-0.174***	-0.177***	-0.300***
	(0.048)	(0.060)	(0.047)	(0.046)	(0.101)
Female*Early GPA		-0.067			
		(0.094)			
Black	-0.031	-0.012	-0.019	-0.017	-0.024
	(0.070)	(0.070)	(0.069)	(0.068)	(0.068)
Hispanic	0.107	0.097	0.091	0.089	0.086
	(0.074)	(0.073)	(0.072)	(0.071)	(0.071)
Asian	0.066	0.061	0.060	0.059	0.061
	(0.103)	(0.102)	(0.101)	(0.100)	(0.100)
AFQT	-0.043	0.021	-0.029	-0.025	0.019
	(0.027)	(0.036)	(0.028)	(0.027)	(0.046)
Female*AFQT		-0.139***			
		(0.050)			
First Major Characteristics:					
Grading std			-0.060		
			(0.095)		
Avg SAT Math			-0.105		
			(0.099)		
Male pct			-0.066		
			(0.089)		
Black pct			-0.045		
			(0.103)		
Hispanic pct			0.018		
			(0.082)		
Asian pct			0.003		
			(0.123)		
Competitiveness				-0.205***	-0.203***
				(0.039)	(0.039)
AFQT*Competitiveness					-0.047
					(0.040)
Early GPA*Competitiveness					0.113
					(0.082)
Constant	0.311***	0.286***	0.535***	0.540***	0.543***
	(0.037)	(0.038)	(0.063)	(0.057)	(0.057)
Observations	413	413	413	413	413
R-squared	0.085	0.108	0.146	0.144	0.149

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Note: The sample includes all students who graduated from a four-year college and had a valid AFQT score and GPA, who first reported a STEM major. The dependent variable is a dummy for switching out of STEM. Early GPA is average GPA in the first two years of college. GPA is de-meaned so that the main effect is the effect at the mean GPA. The AFQT score is in standard deviations. Average SAT math is the average SAT math score in the major, from the Baccalaureate and Beyond. Grading standards are calculated as the difference between the major's SAT total score rank and its average GPA rank, from the Baccalaureate and Beyond. The gender and race percentages are the makeup of the major as calculated in the ACS, in standard deviations. Competitiveness is the average of Asian percentage, grading standards, and average SAT math.

students who switch to business – a large course content change but a less dramatic change in gender makeup – are male.[54]

Our last set of results looks at the direction of change in major non-course characteristics (m^θ) and major course characteristics (m^x) when students leave STEM fields. In Table 11, the constant terms show that the average STEM leaver moves to a less male, less Asian, less competitive major. This is unsurprising given that they are leaving fields high in those characteristics. The only significant gender differential here is grading standards – women who leave STEM seek easier-grading majors than men do – although the point estimates also suggest that women seek out lower-achieving peers and more female-heavy majors to a greater degree than men do.

Table 11
Direction of Switching, for STEM Leavers (Non-Course Characteristics)

	Dependent Variables: Change in Major Characteristic From Old to New Major							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Avg SAT M	Grading	Male pct	White pct	Black pct	Hisp pct	Asian pct	Competitiveness
Female	-0.177	-0.257**	-0.138	0.021	-0.091	-0.121	0.024	-0.079
	(0.132)	(0.127)	(0.140)	(0.137)	(0.172)	(0.176)	(0.099)	(0.091)
Black	-0.078	-0.308*	-0.359**	-0.178	0.171	-0.222	0.197	-0.173
	(0.178)	(0.172)	(0.179)	(0.180)	(0.234)	(0.239)	(0.130)	(0.122)
Hispanic	0.120	-0.024	0.037	-0.136	0.160	0.259	0.017	0.062
	(0.176)	(0.170)	(0.178)	(0.178)	(0.230)	(0.236)	(0.129)	(0.121)
Asian	-0.040	0.241	-0.065	0.025	0.146	-0.091	-0.031	0.124
	(0.266)	(0.257)	(0.268)	(0.269)	(0.348)	(0.357)	(0.194)	(0.182)
High AFQT	0.285*	0.338**	0.307**	-0.033	-0.216	-0.175	0.143	0.245**
	(0.145)	(0.142)	(0.146)	(0.148)	(0.195)	(0.196)	(0.106)	(0.099)
Early GPA	-0.048	-0.169	-0.250*	0.030	0.016	-0.073	-0.013	-0.103
	(0.128)	(0.124)	(0.129)	(0.129)	(0.168)	(0.172)	(0.094)	(0.088)
First major's value of dependent variable	-0.894***	-0.956***	-0.882***	-0.908***	-0.952***	-0.841***	-0.947***	-0.962***
	(0.078)	(0.090)	(0.067)	(0.077)	(0.121)	(0.121)	(0.052)	(0.065)
Constant	-0.415**	-0.394**	-0.385**	0.304	0.301	0.436*	-0.459***	-0.480***
	(0.167)	(0.154)	(0.173)	(0.186)	(0.206)	(0.224)	(0.137)	(0.120)
Observations	149	149	149	149	149	149	149	148
R-squared	0.499	0.476	0.584	0.516	0.315	0.269	0.722	0.626

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: The sample is all students who switched out of STEM. The dependent variables are the change in each major characteristic, all measured in standard deviations. Early GPA is average GPA in the first two years of college. "High AFQT" is a dummy for being in the top half of the AFQT distribution. Average SAT math is the average SAT math score in the major, from the Baccalaureate and Beyond. Grading standards are calculated as the difference between the major's SAT total score rank and its average GPA rank, from the Baccalaureate and Beyond. The gender and race percentages are the makeup of the major as calculated in the ACS, in standard deviations. Competitiveness is the average of Asian percentage, grading standards, and average SAT math.

[54] Business is actually the most common destination for both male and female STEM leavers, because it is a large major in general, but the percentage of female switchers who go to business is less than half as large as the percentage of male switchers. Meanwhile, the percentage of female switchers going to nursing is almost seven times larger than that of male switchers.

Table 12
Direction of Switching, for STEM Leavers (Course Characteristics)

	Dependent Variables: Change in Major Characteristic From Old to New Major						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Math	Humanities	For Lang	Sci/Engin	Edu	Business	Soc Sci
Female	-0.063	-0.222	-0.016	0.049	0.143	-0.136	-0.211
	(0.055)	(0.170)	(0.175)	(0.086)	(0.155)	(0.177)	(0.182)
Black	0.016	-0.146	-0.259	0.131	0.098	-0.432*	-0.038
	(0.074)	(0.224)	(0.220)	(0.117)	(0.205)	(0.233)	(0.242)
Hispanic	0.031	0.174	-0.072	-0.045	0.002	-0.041	0.134
	(0.073)	(0.223)	(0.219)	(0.118)	(0.202)	(0.231)	(0.242)
Asian	-0.009	-0.338	-0.296	-0.027	-0.239	0.090	0.265
	(0.110)	(0.334)	(0.331)	(0.175)	(0.307)	(0.358)	(0.362)
High AFQT	0.035	0.125	0.022	0.048	-0.173	0.243	0.082
	(0.060)	(0.182)	(0.182)	(0.097)	(0.166)	(0.193)	(0.198)
Early GPA	0.008	-0.034	0.050	0.013	0.265	-0.048	0.206
	(0.079)	(0.271)	(0.173)	(0.117)	(0.195)	(0.188)	(0.251)
First major's value of	-0.979***	-0.609***	-0.844***	-0.919***	-1.724***	-0.291***	-0.393***
dependent variable	(0.026)	(0.168)	(0.186)	(0.036)	(0.162)	(0.164)	(0.199)
Early GPA*First value	-0.061	-0.238	0.418	0.041	0.535	0.837***	0.588**
	(0.059)	(0.498)	(0.335)	(0.066)	(0.472)	(0.299)	(0.364)
Constant	-0.344***	0.171	0.050	-0.406***	-0.010	0.319	0.390
	(0.071)	(0.212)	(0.205)	(0.106)	(0.187)	(0.205)	(0.243)
Observations	149	149	149	149	149	149	149
R-squared	0.913	0.176	0.175	0.842	0.177	0.149	0.067

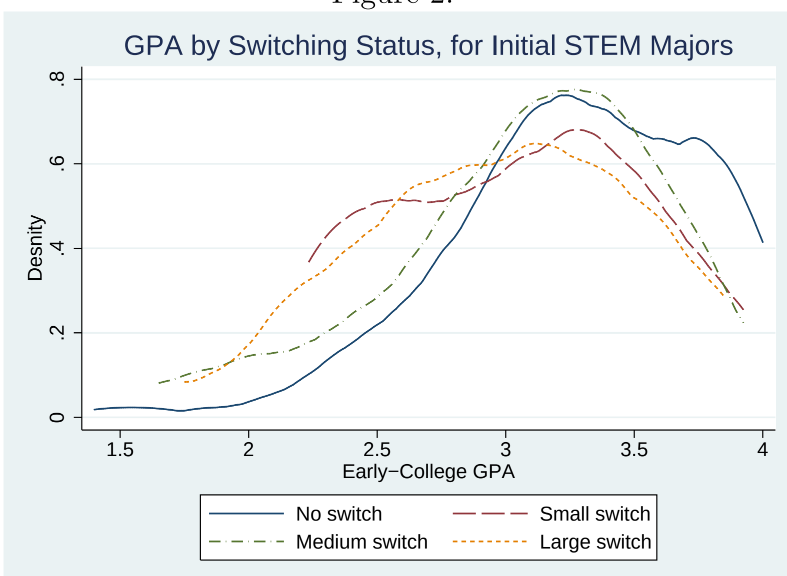
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: The sample is all those who switch out of STEM fields. The dependent variables are the changes in major course content, all measured in standard deviations. Course content is the average number of courses in each field taken by a graduate in that major. Early GPA is average GPA in the first two years of college. GPA is de-meaned so that the main effect is the effect at the mean GPA. "High AFQT" is a dummy for being in the top half of the AFQT distribution.

Table 12 does the same for the course characteristics. All students who leave STEM are going to lower-math, lower-science majors, but there are no significant differences between the men and women who are leaving STEM.

We saw in Table 10 that female STEM leavers were a bit different from male STEM leavers: the females were going to less competitive, easier-grading, less male-heavy majors than the males. In Table 12, there is no such difference for the course characteristics. Recall that for all major switchers (Table 9), female switchers sought out majors with less math and science content than male switchers did. Here, restricting to those leaving STEM, there is no such gender difference. Thus, it seems that females are more likely to leave STEM because of the competitive "culture" and difficulty of the major, not because of the science and math content. This lends some credibility to theories of gender differences in competitiveness (Niederle and Vesterlund 2011) and also to psychology literature emphasizing the importance of matching on personality type (Holland 1966, Smart et al. 1999).

Finally, Figure 2 visualizes some of these results, looking at GPA distributions for initial STEM majors who do not switch majors, those who make small switches (e.g., nursing or medical/health services), those who make medium-sized switches (e.g., psychology or philosophy), and those who make the largest switches (e.g., education or business). The non-switchers have the highest average early GPAs (3.30), with the small and medium switchers behind at 3.05 and 3.08, respectively. The students making the largest switches have an average GPA of 2.98. Clearly there is a relationship here between grades and distance of switch, even if it is not monotonic.[55]

Figure 2:



Our results imply that while academic preparation matters, the *gender gap* in switching out of STEM seems more driven by preferences than by academics. Many well-prepared women who have fine grades are still leaving STEM majors and seeking out less competitive, easier-grading majors. Initiatives that help women be better prepared for science fields may help grow the number of women in STEM, but other factors may still lead them to switch out.

[55]This figure includes both men and women, but it is almost identical when restricted to women.

6 Conclusion

We have provided the first comprehensive analysis of major switching among college students. Major switching is common, with 37% of graduates finishing in a different major than the one they started in, but not all major changes are created equal. Some students make “major changes” – switching from one major to a major with radically different course content. Other students switch to majors that are similar in course content but very different in non-course characteristics. Studying these patterns helps us understand students’ motivations and preferences.

Grades, gender, and preferences are all determinants of major switching. Students with low grades switch majors more - and the lower the grades, the larger the switch. Competitive majors drive away lower-ability women but have little or no effect on higher-ability women or men of any ability level. All types of students who switch majors move toward majors that “look like them”. One possible explanation is that some students switch to find their preferred peer group, not just their academic match.

Women are much more likely than men to leave STEM, but they are not fleeing science and math any more than the men are. Rather, they are fleeing competitive, difficult, male-dominated majors. The gender gap in switching out of STEM is not driven by differences in ability or grades between men and women, but by differences in preferences. Many women who are perfectly competent in STEM fields still switch out, seeking other science-related majors that are less male-heavy and less competitive, such as nursing.

While our results are descriptive and only suggestive of the underlying mechanisms, they can still inform the discussion surrounding women in STEM. Colleges and policymakers must be aware of both the academic and non-academic motivations for switching. Preparing women better for science-related fields, for example, can help them be better-matched academically with those fields when they arrive in college, making them more likely to stay. However, this is only part of the story, as our analysis shows. Many well-prepared women who arrive in STEM fields and enjoy science but dislike male-dominated, competitive majors may still be unlikely to stay.

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Appendix Tables

Table A1

Correlations Between Major Characteristics

Major measure:	Avg SAT M	Grading	Male pct	White pct	Black pct	Hisp pct	Asian pct
Avg SAT M	1.00						
Grading	0.66	1.00					
Male pct	0.57	0.78	1.00				
White pct	-0.37	-0.06	-0.20	1.00			
Black pct	-0.36	-0.45	-0.39	-0.44	1.00		
Hispanic pct	-0.10	-0.39	-0.33	-0.35	0.63	1.00	
Asian pct	0.59	0.41	0.52	-0.74	-0.21	-0.30	1.00

Note: All measures are in standard deviations. To take the correlations, we use one observation per major so that all majors are weighted equally. SAT math is the major's average SAT math scores, from the Baccalaureate and Beyond. Grading is the major's grading standards, calculated as the difference between the major's SAT total score rank and its average GPA rank, from the Baccalaureate and Beyond. The gender and racial percentages are calculated from the American Community Survey 2009-2014, using graduates from 2003 to 2008.

Table A2

Destinations of STEM Leavers

	Percentage of Switchers Going to Each Major		
	All Switchers	Male Switchers	Female Switchers
Agriculture	2.7	2.9	2.5
Fitness and Nutrition	1.4	0.0	2.5
Other Med/Health Services	9.5	5.9	12.5
Family and Consumer Science	0.7	1.5	0.0
Communications	5.4	4.4	6.3
Nursing	4.7	0.0	8.8
Art History and Fine Arts	8.1	8.8	7.5
Architecture	0.7	1.5	0.0
Philosophy and Religion	1.4	2.9	0.0
Social Work	1.4	1.5	1.3
Other Social Sciences	5.4	2.9	7.5
Protective Services	0.7	1.5	0.0
Public Administration and Law	2.0	1.5	2.5
Psychology	11.5	14.7	8.8
Area Studies	1.4	0.0	2.5
Economics	2.0	1.5	2.5
Business	25.0	32.4	18.8
English/Literature	2.0	2.9	1.3
History	0.7	1.5	0.0
Political Science	3.4	5.9	1.3
Education	8.1	4.4	11.3
International Relations	1.4	1.5	1.3
Foreign Language	0.7	0.0	1.3

Note: The sample is all those who switched out of STEM majors. Column 1 gives the percentage of the sample going to each destination major. Column 2 does the same for males, and column 3 for females. Majors are listed from closest to STEM fields to farthest away from the average STEM field, as measured by our angular academic distance measure, described in Section 3.