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

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Abstract

Almost half of college students switch majors at least once, suggesting that college major choice is a process rather than a single decision. This paper provides the first comprehensive analysis of major switching, modeling the choice process as a complex matching problem between student and major. Students have abilities and preferences, while majors have both academic course requirements and nonacademic characteristics such as competitiveness and gender makeup. We first show that low grades serve as a signal of academic mismatch. Low grades predict switching majors - and the lower the grades, the "larger" the switch in academic terms. When students switch majors, their grades improve - and the larger the switch, the greater the improvement. Academics are only one factor in major switches, however. Overwhelmingly, when students switch majors, they are drawn to majors that "look like them": females to female-heavy majors, blacks to black-heavy majors, and so on. Part of the major choice process seems to be finding one's preferred peer group. Women also flee competitive majors – especially STEM majors – at much higher rates than men. Women who leave

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STEM switch to majors that are much less male-dominated, suggesting that leaving STEM is more about fleeing the culture and makeup of STEM majors than it is about fleeing science.

1 Introduction

College major choice is one of the most-studied topics in labor economics and the economics of education. Most studies have treated major choice as a single decision, determined by such factors as academic preparation, preferences, and labor market conditions. However, almost half of students who complete a degree switch majors during their time in college.[1] This suggests that the choice of college major is better understood as a process rather than a single decision. It also suggests that college is a learning process, in which students acquire information about themselves and about majors. This paper studies major switching as a stage of that process.

In this paper, we provide the first comprehensive analysis of major switching among college students, modeling the choice process as a multidimensional matching problem between student and major. 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 academic requirements and nonacademic characteristics. We show that both of these dimensions matter a great deal. Some major changes represent "major changes" of academic and life direction, while others are smaller course corrections, and both grades and personal characteristics predict which type of switch will occur. We also provide a detailed analysis of STEM fields, which are of particular policy interest and have high net switch-out rates, particularly among women.

For a college graduate, the major choice process is the beginning of the career search, which has been studied extensively by economists. One approach is to model career search as a matching problem between worker and occupation, in which there

[1] See NCES (2013) at http://nces.ed.gov/pubs2014/2014001rev.pdf

is a cost to being mismatched.[2] We think of the choice of major in a similar way, as a matching problem between student and major. As students learn about themselves and about majors, they may be induced to change to a different major just as one would change to a different occupation. Moreover, the match between student and major is a complex one, as majors differ in both academic and nonacademic characteristics, such as their level of competitiveness or gender makeup.

Major switching is common; in our data, 42% of students who finish college change majors at least once. We show that one primary reason for this is grades, which serve as a signal of how well the student is matched with her major academically. Low grades predict switching majors - and the lower the grades, the "larger" the switch. When students switch majors, their grades improve - and the larger the switch, the greater the improvement. Low grades signal an academic mismatch of student and major, and a major switch represents a correction to a better match.

Academics are only one factor, however. Overwhelmingly, when students switch majors, they are drawn to majors that "look like them": females to female-heavy majors, whites to white-heavy majors, blacks to black-heavy majors, and so on. It appears that the major choice process is partly about finding your preferred peer group, not just your academic match. Competitive majors also drive many women away, and particularly women with lower test scores. The gender effect is so strong that even a woman with high test scores is more likely to leave a competitive major than a man with low test scores. This is consistent with other research showing that women shy away from more competitive environments.[3]

Switching out of STEM (science, technology, engineering, and mathematics) majors is driven more by preferences and culture than by academics. Low grades predict leaving STEM, but gender is the largest predictor: women are about 75% more likely to leave STEM than men are, and none of this is explained by grades. Women do not disproportionately flee STEM majors because a lack of academic competence. Nor is it because they do not like science: when women leave STEM, they often move to majors similar in academic content but very different in gender makeup and competitiveness, such as nursing. Colleges seeking to retain more women in STEM fields must be

[2]See, for example, Neal (1999) and Guvenen et al. (2015).

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

concerned about more than just academic factors.

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.[4] Majors, similarly, are a vector of academic (course) requirements and nonacademic characteristics. Majors are not "ranked" from best to worst in any way, but rather the goal of a student is to find her best match.

Information frictions can lead to initial mismatch between the student and her major. Students enter college unsure about both their own abilities and the nonacademic characteristics of majors. In college, they learn about their abilities through grades and about the characteristics of majors, which may induce them to switch majors. There are two sources of mismatch that lead to switching: academic/ability mismatch and preference mismatch. Our results suggest that both are important.

Our results also confirm that the college major choice should be analyzed as a process rather than a single decision. Combined with results from Speer (2016), who shows that pre-college ability factors explain much of the gender gap in major choice (particularly in STEM fields) but little of the gap in major switching, it is clear that different factors matter at different stages of this choice process. The switching decision is a key part of the final college major outcome and is important for understanding gender gaps in major.

Researchers have long recognized the choice of major as an important determinant of a worker's occupational and earnings prospects. Many factors have been identified as influencing the major decision, 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), and the impact of peers and advisors (Ware and Lee 1988).

A large literature also looks at gender gaps in college major, some of which are substantial (Speer 2016). While racial gaps in major also exist, Dickson (2010) shows that the gender gaps are much larger, and these gaps contribute to the male-female wage gap (Brown and Corcoran 1997). Most papers studying the determinants of

[4]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. This is what we mean by "abilities" from this point on in the paper.

gender gaps have found that differences in academic preparation can explain only a small portion of gender gaps in major,[5] although recent work by Speer (2016) uses more extensive data to show that preparation can explain a large portion of some of these gaps, including gaps in STEM fields.

Besides ability and preparation, researchers have proposed many other explanations for gender gaps in major. Evidence shows that women are less competitive and shy away from competitive majors (Niederle and Vesterlund (2011), Buser, Niederle and Oosterbeek (2014)). The gender of the professors may also matter (Carrell, Page and West 2010), although some studies find either minor effects (Hoffmann and Oreopoulos 2009) or no effect (Price 2010). There is some evidence that women are more responsive to grades than are men and may be discouraged from studying difficult fields because of this (Ost 2010).

Crucially, almost all of the college major literature has treated the choice of major as a single decision. However, almost half of college students change their major at least once during college (NCES 2013). A few papers have recognized and tackled this issue. Altonji (1993) and Arcidiacono (2004) model major choice under uncertainty about ability and outcomes, and their models allow students to change majors when they acquire new information. Using unique data from Berea College, Stinebrickner and Stinebrickner (2013) study the process of major choice with a particular focus on how initial beliefs and new information influence major choice and major switches. They find that students enter college overoptimistic but then acquire more accurate information about their abilities while in college, which leads some students to leave difficult majors. To understand the major decision process, we must think about the information that students have when they enter college and the information they acquire in college.[6]

A few other recent papers motivate our analysis. Hsu (2016) also thinks of college major completion as a process, studying how students make progress toward various potential degrees. Our paper shares some elements with his, as we also think of a major

[5]See Turner and Bowen (1999), Daymont and Andrisani (1984), Arcidiacono (2004), and Zafar (2013) for examples.

[6]A related, but separate, issue is the timing of specialization in college, which varies significantly across countries. This can affect how well-matched a student is with her major and eventual field of work (Malamud (2010),Bordon and Fu (2015)).

as a bundle of courses and study how students respond to grade signals in choosing majors. Hsu (2016) studies only one university and does not consider "distance" or "direction" of major switches, nor does he focus on gender differences. Fischer (2016) uses the random assignment of freshmen to introductory science courses at one university to study the effect of being assigned to a higher-achieving class. She shows that women are deterred from studying STEM fields if they are assigned to a higher-achieving class, while men are unaffected. Our results are consistent with her findings. She does not look at distance or direction of switches, or analyze the destinations of the STEM switchers. Zölitz and Feld (2016), studying a single university in Europe, show that the gender composition of randomly assigned first-year teaching sections has persistent effects on major choice. Women who are assigned to sections with more females are more likely to choose female-dominated majors.

Finally, Speer (2016) studies the overall college major decision and switching out of STEM as separate topics. He finds that while pre-college preparation (test scores) can explain a good portion of gender gaps in college majors, especially in STEM fields, it cannot explain much of the gender switching gap. This confirms to us that college major choice should be thought of as a process, in which different factors matter at different stages. We expand on the switching section of Speer (2016) to provide a comprehensive analysis of major switching.

This paper synthesizes the prior literature on major switching in a comprehensive framework, largely confirming their results and providing new ones. We develop the concepts of "distance" and "direction" of switching in our analysis, which yield important new insights into the motivations for switching. In particular, we provide some needed clarity on the gender gap in switching out of STEM fields.

The paper proceeds as follows. Section 2 presents a model of major choice and major switching, in which students match with majors on academic and nonacademic components. 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 discusses a potential addition to the analysis, and Section 7 concludes.

2 Model

In this section, we present a two-period matching model of college major choice. 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.[7]

We will not estimate this model, but it will motivate the data construction and empirical analysis, and help us interpret the results that we find. We will summarize the model's implications in Section 2.5, which point us toward the empirical analysis.

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 nonacademic aspects of a college major, such as competitiveness or race/gender makeup. The s^θ components represent students' ideal value of each major characteristic. A student's preferences stay constant throughout college.

Students can perfectly observe their own preferences s^θ, but not their own ability s^x. Instead, they have beliefs about their abilities given by $\hat{s}^x$, where $\hat{s}^x$ is normally distributed around the true ability s^x. We can think of these beliefs at the beginning of college as a combination of high school grades, SAT scores, and other pre-college factors.[8]

[7]While we do not discuss post-college earnings explicitly, we implicitly assume that an individual's career outcomes depend on the quality of the job's match to the individual's abilities. This is explored in Guvenen et al. (2015), who find that there is a cost to a worker being mismatched with her job. The college major literature also makes clear that students' major choices depend on preferences, not just earnings returns (e.g., Zafar (2013), Arcidiacono (2004)). In our model, students match with majors based on both the academic characteristics (ability) and on preferences. The major choice is thus partially based on future earnings but also on utility during college. In Section 6, we discuss how one would include earnings more explicitly.

[8]The true s^x, which represents a student's true ability relative to the entire student population, is not observable to students or to the researcher. There are many reasons why students' beliefs may

A major is also a vector m with two components. The first component, m^x, denotes the academic (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 and nonacademic or cultural characteristics of the major.[9]

To be clear, m^θ represents the actual nonacademic 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.

We make two assumptions that are worth mentioning. First, majors are "large" 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. Second, students' preferences are single-peaked. The closer the major is to the student's ideal, the happier the student is.

Given our definitions of students and majors, and assuming that the model has full support of majors, for each student s there is an ideal major m^I.[10] The ideal major is one that matches both the student's abilities and preferences on all components:

$$m^I = \{(m^{Ix}, m^{I\theta}) | m^{Ix} = s^x, m^{I\theta} = s^\theta\}. \tag{1}$$

Frictions arise due to two sources of information inaccuracy at the time of decision making. First, students do not perfectly observe their own abilities s^x, but form beliefs about their abilities as they acquire new information using Bayes' rule. Students enter college (period 1) with prior beliefs about their own abilities $\hat{s}^x_0$. Second, at college entry, students can observe all ability requirements m^x for all majors, but not the nonacademic components m^θ of majors. For these two reasons, students may be mismatched with the major they first choose.[11]

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not be accurate upon college entry. For one, they may judge their ability against their classmates prior to college (Murphy and Weinhardt 2016), not realizing that their primary or secondary school is not representative of the population.

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

[10] So that the elements of s^x and m^x are comparable, one can think of them as being measured in standard deviations. So the s^x math element represents the student's z-score in math among all students, and the m^x math element represents the major's z-score in math among all majors (and so on). Since s^θ represents the student's ideal m^θ, these elements are already in the same units.

[11] It is realistic that a student would know m^x for all majors, as these would be readily available in the course catalog or on the department's website. Meanwhile, m^θ components – such as the gender

If a student chooses a major that requires abilities different from her own abilities, she will get disutility from being mismatched. A student's expected disutility of being mismatched academically (the x component) is equal to the distance between the major requirements m^x and the student's belief about her own abilities $\hat{s}_0^x$, denoted by $D(m^x, \hat{s}_0^x)$. Similarly, the disutility from being mismatched on preferences (the θ component) is equal to the distance between the major characteristics m^θ and the student's preferences s^θ, denoted by $D(m^\theta, s^\theta)$.[12]

As the student has no information about major characteristics m^θ, she does not consider this in her initial major decision.[13] Rather, she will choose a major to match her beliefs about her own abilities. Her initial major choice will thus be m^*, where $m^{*^x} = \hat{s}_0^x$.

After the first period, students receive two types of new information. First, they observe the nonacademic components 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. 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

$$\hat{s}_1^x = \lambda g^x + (1 - \lambda)\hat{s}_0^x \tag{2}$$

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

makeup of the major or how competitive it is – are difficult to observe without experiencing the major in the classroom. All conclusions in our model stay the same if we instead assumed that students have an imperfect initial belief about m^θ rather than no information, but this would not add any new insights to the model.

[12]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.

[13]In reality, students likely have some idea of a major's characteristics before they arrive in college. One could add prior beliefs about m^θ to the model, but this would leave the model's logic unchanged while adding complexity.

2.2 Major Switching

After students observe this new information, they may realize they are mismatched with their major either on abilities or on preferences. The ability/academic mismatch is revealed through grades. The initial major choice depended on the student's beliefs about her abilities, but now the feedback provided by their grades may change those beliefs. Also, since major choice in the first period is based only on academic requirements (because m^θ is not initially known), students can find that they are mismatched in the culture aspect of their chosen major.

Students have the option to switch from major m^* to major $\tilde{m} \neq m^*$ at a cost. The cost of switching majors is 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:

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

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:

$$\alpha_x D(m^x, \hat{s}_1^x) + \alpha_\theta D(m^\theta, s^\theta) + \alpha_c D(m^{*^x}, m^x) \tag{4}$$

where α_x, α_θ, $\alpha_c > 0$ are the sensitivities to abilities mismatch, preference mismatch, and major-switching costs, respectively.[14]

[14] 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.

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

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

From this expression, we can see that the probability of switching depends on several factors.[15] These factors are early-college grades, initial preference mismatch, and sensitivity to being mismatched.

First, lower grades lead to a higher probability of switching majors. Lower early-college grades signal academic mismatch with the initial major; they tell us that the term $D(m^{*^x}, \hat{s}_1^x)$ is larger, and thus the left side of the expression is larger. Second, switching depends positively on the degree of initial θ mismatch $D(m^{*^\theta}, s^\theta)$. The more mismatched a person is on nonacademic characteristics, the more likely she is to switch majors.[16] Third, those with higher sensitivity to being mismatched (higher α_x and/or α_θ) are more likely to switch majors.[17]

Given the fact that switching cost is not related to the change in 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 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 academic requirements ($\tilde{m}^x = \hat{s}_1^x$).

2.3 Distance of Switching

We can rewrite Expression (5) as

[15] More precisely, we are discussing the probability of switching to major $\tilde{m}$, where $\tilde{m}$ is the major that minimizes Expression (4).

[16] Note that with full support of majors, every student will switch, because it is costless to find the perfect m^θ in period 2. In reality, there is not full support, so only students who are "mismatched enough" to justify the switching cost will switch majors. Adding an exogenous administrative cost of switching majors would have the same effect without altering the model's conclusions.

[17] We can see this in Expression (5) 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.

$$D(m^{*^x}, \tilde{m}^x) \leq \frac{\alpha_x}{\alpha_c}\Big[D(m^{*^x}, \hat{s}_1^x) - D(\tilde{m}^x, \hat{s}_1^x)\Big] + \frac{\alpha_\theta}{\alpha_c}\Big[D(m^{*^\theta}, s^\theta) - D(\tilde{m}^\theta, s^\theta)\Big] \tag{6}$$

The term on the left-hand side is the distance moved in academic terms in 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 academic or preference 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 bear the major-switching cost in order to improve each type of mismatch. The first part of this statement – that the larger the initial academic mismatch, the greater distance the student is willing to move – is intuitive. 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).

It is a bit more puzzling that a larger initial mismatch in preferences ($D(m^{*^\theta}, s^\theta)$) also allows a student to make a larger switch in x terms. In fact, with full support of majors, this is irrelevant, because the student can always find a major with the same m^x and a different m^θ and pay no switching cost. If, however, there is not full support of majors, then this makes more sense. A student wishing to switch to a major with a different m^θ value might have to settle for a different m^x as well, and thus a larger initial mismatch in θ would be required to justify such a move.

Given this, it is straightforward to show that, holding everything else constant, 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 academic terms from their initial major choice. We now have two predictions about grades and major switching. Lower grades should raise the probability of switching, and lower grades should also increase the distance of switching for those who switch.

2.4 Direction of Switching

Finally, we are interested in the "direction" of major switching. Once students learn that they are mismatched, will they 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 academic (x) and preference (θ) components. In fact, since there is no cost of switching in the θ component, the new major will always be her perfect match in terms of θ.[18]

To see why, consider element j (e.g., math) of the student's updated beliefs about her abilities $\hat{s}_1^x$ and the initial major's academic requirements m^{*^x}.[19] Suppose that in period 1, the student receives poor math grades – she finds that $\hat{s}_{1j}^x < m_j^{*^x}$. The major requires more math than she would like, given her updated beliefs. She now has the option to switch to a new major $\tilde{m}$ with math requirement $\tilde{m}_j^x$.

Clearly, she will not choose a new major $\tilde{m}$ with $\tilde{m}_j^x > m_j^{*^x}$ – a major that requires even more math than her initial choice. This is because she would prefer staying at her initial major m^* to moving to major $\tilde{m}$. Moving to major $\tilde{m}$ would incur a switching cost *and* would be a greater distance from her updated beliefs than her current major is, while staying at her current major incurs no switching cost.

Similarly, she will never switch to a new major $\tilde{m}$ with $\tilde{m}_j^x < \hat{s}_{1j}^x$ – she will not "overshoot" by choosing a new major with even less math than her updated beliefs. This is because she would always prefer to switch to a major with the ideal level of math requirements ($m_j^x = \hat{s}_{1j}^x$) rather than overshooting, which would incur a greater switching cost and carry a disutility of mismatch, while moving to a major with ideal math requirements would bring no disutility. We can thus conclude that her second major choice $\tilde{m}$ will be such that

$$\tilde{m}_j^x \in [\hat{s}_{1j}^x, m_j^{*^x}]$$

[18] This comes from the full support of majors and the lack of a switching cost related to the change in θ characteristics. If there is not full support of majors, then students may face a trade-off between improving their academic 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.

[19] Note that because there is a full support of majors, we can think about each element of the vector separately, holding the other elements constant.

No student should switch to a worse academic match. So long as the sensitivity to switching costs α_c is not too large, every major switch that occurs should be an improvement in match for every element of the ability/academic x vector.[20]

This provides us with another testable prediction: grades will not go down after a major switch – and most likely will improve.[21] Any student who switches to a new major with different academic requirements should be better-matched academically in her new major than she was in her old major, and thus we should expect her grades to be better in the new major than they were in the old major.

We can also say that the larger the distance of a switch, the larger should be the improvement in grades. Since students are always switching toward better matches, a larger move means that the student is getting closer to her new beliefs. How close she gets depends on the cost of switching and her sensitivity to that cost (α_c), but it is clear the a larger major switch should be associated with a larger improvement in grades.

For the preference (θ) components, the argument is even simpler, because there is no cost of switching to a different m^θ. The student will choose new major $\tilde{m}$ where $\tilde{m}_k^\theta = s_k^\theta$, for all elements k. This is a perfect match, and thus cannot be a worse match than where she started.

To sum up, major switches should bring improvements in both academic and preference matches. We should observe that grades improve (or at least do not go down) after a major switch. Because we as researchers do not observe people's preferences, we take the major switches that we observe as a form of revealed preference. If we observe that women switch to majors that are less competitive, that tells us that women prefer less competitive majors – but this is a finding, not an assumption that we make. We do not put any restriction on students' preferences for nonacademic aspects of majors.

2.5 Summary of Model Implications

Let us now summarize the implications of our model.

[20] A formal proof of this argument is simple to construct and is available upon request.

[21] If the cost of switching is too high, then students will stay at the same m^x they started at, in which case grades should stay constant in the second period. In all other cases, grades should improve with a switch.

1. Probability of Switching Majors

    - *Major switching should depend negatively on early-college grades, positively on initial preference mismatch, and positively on the student's sensitivity to being mismatched on both the academic and preference components.*

2. Distance of Switches

    - *Students with lower early-college grades should make larger academic switches. Lower grades represent academic mismatch between the student and the major, so the lower the grades, the larger the correction to be made.*

3. Grade Improvement

    - *Grades should improve (or stay constant) when students switch majors, and grades should improve more the larger the distance of switch.*

4. Switching Patterns and Preferences

    - *Since all switches should represent match improvements, the switching patterns we observe in the data can tell us something about why students choose to switch majors. If most switching can be explained by grades, then it is likely that academic mismatch is driving switching behavior. If grades explain little, then most switching is being driven by preference mismatch. Further, the switching patterns we see in the data reveal the students' preferences over major characteristics.*

3 Data

Our primary data source is the National Longitudinal Survey of Youth 1997 (NLSY97). The NLSY97 (hereafter NLSY) is a nationally representative panel data set of 8,984 individuals born between 1980 and 1984. They were aged 12 to 17 when first interviewed in 1997 and have been interviewed every year from 1997 through the present. The

NLSY contains standard demographic information as well as a measure of cognitive skills, the AFQT score.[22]

The NLSY contains detailed information on the college experience for respondents who attended college, including information on college majors and grade point averages. For each college attended in each academic term, respondents are asked their major field of study (with about 35 options to choose from) and their GPA. It is thus straightforward to construct a time series of majors and grades for each respondent. We measure major switching by recording the first reported major (not counting "No major") and the final reported major before graduation. We call it a major switch if the two are different. One might be concerned that students report several majors along the way and that the first one is merely a guess at what the student thinks she is interested in. However, 90% of students report three or fewer majors, and our switching rates are similar to national averages reported by the Department of Education.[23] This suggests that the major reports are reliable.[24]

Some researchers have used data from a single university to study major switching (e.g., Stinebrickner and Stinebrickner (2013), Fischer (2016)). This has some advantages, like access to information on classmates and more detailed grade information. Our approach in using the NLSY is more comprehensive and more generalizable to the whole population of college students.[25]

We construct a GPA measure for each year the student was in college.[26] We define "early GPA" as the average GPA in the years before the student switched majors, and "late GPA" as the average GPA in the years after the switch. If a student did not switch majors, we use the first two years and last two years. The average time of

[22]The AFQT was given to survey respondents in 1999. Scores are age-adjusted. We include the AFQT in our analysis because it may be correlated with a student's preferences.

[23]NCES (2013) http://nces.ed.gov/pubs2014/2014001rev.pdf

[24]One might also be concerned that misclassification error overstates the number of major switches, just as it is widely believed to overstate the number of occupational changes (e.g., Neal 1999). Our method of classifying major switches mitigates this problem somewhat. If a student is coded as switching from major A to major B and then back to major A (which may indicate that there was never a real change), we do not code this person as a switcher, as her first and last majors are the same. Note also that we are using student reports of their major, not administrative data on officially declared majors.

[25]We have experimented with linking the NLSY to IPEDS data on the colleges attended by each respondent, but our sample sizes are too small to draw any conclusions about differences across college types.

[26]If a student reports attending two different colleges in that year, we average the two GPA measures.

switching (among switchers) is after 1.85 years of college, and this does not differ by gender. The downside of the grade data is that the grades are not linked to specific courses or subjects. We are left to assume assume that the grades for a given term give the student information about her ability in the major she reports for that term. This is reasonable if the student is taking classes in that major or in closely related fields.

Table 1 shows summary statistics for our sample of college graduates.[27] In our data, 42% of college graduates switch majors, and the switch-out rate is similar for STEM fields.[28] Grades improve on average as students go through college. AFQT is standardized for the whole population, so the positive mean of AFQT tells us that college graduates have above average cognitive skill.

We also need both academic and nonacademic characteristics of majors. The academic portion of a major (m^x) is a vector of course requirements. We get this information from the Department of Education's Baccalaureate and Beyond data set. 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.[29]

Nonacademic characteristics of a major (m^θ) include its competitiveness and race and gender makeup. We measure competitiveness as the average SAT math score in the major, also taken from the Baccalaureate and Beyond data.[30] While the true level of competitiveness in a major is unobservable, we believe average test scores of its

[27]The college dropout decision is also interesting has been analyzed by Stinebrickner and Stinebrickner (2014), but we see this as fundamentally different and more complex than the decision to switch majors, as it involves academic factors but also things like credit and financial constraints, personal issues, and lack of parental support. These factors are beyond the scope of our model, and thus we restrict to graduates in our analysis. However, we have done some basic analysis of dropouts and found that (as in Stinebrickner and Stinebrickner (2014)) low grades strongly predict dropping out, and that males drop out more often than females.

[28]Note that "switch out of STEM" does not include those who switch from one STEM field to another. In total, 51% of those who start in STEM switch majors, with 41% switching out of STEM and 10% switching within STEM.

[29]See Speer (2016) 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 1-to-1 match with some of the 51 majors not used.

[30]We have also used an SAT/ACT composite score, which gives similar results.

students is a good proxy.[31] Race and gender makeup of a major are calculated from the American Community Survey as the percentage of graduates from a major who are white, black, Hispanic, and Asian, as well as the percentage that are male and female. In calculating race and gender makeup of majors, we restrict in the ACS to the graduation cohorts representing when most NLSY respondents would have been in college – 2003 to 2008.[32] Thus, our m^{θ} measures are national averages, not college-specific values.[33]

To sum up, for each major, we have academic characteristics – a vector of course requirements – and nonacademic characteristics – competitiveness and race and gender makeup. Table 2 shows a selection of characteristics for our college major categories, in standard deviations for ease of comparison.[34] 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. Also apparent is a strong positive correlation between the male share and the Asian share in a major ($\rho = 0.70$), as well between the male share and the average SAT math score ($\rho = 0.76$).

The benefit of imagining majors as a bundle of characteristics – rather than simply putting them in categories like science or humanities – is that 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

[31]For instance, STEM majors have some of the highest average SAT math scores and are regularly referred to as competitive majors (Fischer 2016). One could alternatively call this the "skill level" of the major, but we prefer the term competitiveness for ease of interpretation. 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, we acknowledge that our measure is imperfect.

[32]We map ACS majors into the 51 B&B categories using a crosswalk we construct.

[33]Of course, there are many other relevant characteristics of a major that we do not have or use, including its family-friendliness, the gender makeup of its faculty, and its returns in the marriage market. We have also calculated 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.

[34]The SAT math score is missing for some smaller majors, due to restricted data.

of the angle between the two vectors. The measure varies between 0 and 1 and equals 0 if the vectors point in the same direction. It 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.[35]

One may wonder why we use this distance measure instead of the Euclidean distance between m^x and $\tilde{m}^x$. There are two reasons. First, the Euclidean distance measures 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 separately. The angular distance better captures our notion that the cost of switching is related to the degree of course overlap in the two majors. If majors A and B have m^x vectors pointing in the same direction, but major B's vector is shorter – that is, they require the same mix of courses, but major B requires fewer of them – then the cost of switching from major B to major A should be zero, as all of the courses from major B will count toward major A. Euclidean distance would show a positive cost of that switch, whereas our measure shows a zero cost.

The second reason is a data limitation. Some less standard course categories are not included in the course data, leaving some majors to add up to a smaller number of courses than others. For instance, nursing, which requires many nursing-specific courses and practicums, is a "short" vector compared to engineering, whose course requirements are mostly accounted for by our data. This means that any move to nursing would automatically look like a large move if using the Euclidean distance measure, even if the first major had a similar mix of courses to nursing in the categories we observe.

To be sure that our results are robust to other distance measures, we will also use an alternative distance measure. We find the "predominant" course category in each major – that is, $\max_j m_j^x$. Our alternative distance measure is equal to 1 if the predominant course categories in the old and new majors are different. If they are the same, the distance is equal to 0.

We can also measure the "direction" of major switches, both in the academic (x) and nonacademic (θ) components. If one switches from major m to major $\tilde{m}$, then the

[35] 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.

direction of switch in element j is

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

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. Note that we do not use the absolute value to measure direction, because the sign of the change tells us something important. An increase in math content, for instance, tells us that the student has learned she is better at math than she previously believed, while a decrease in math content tells us the opposite.

We define direction in the θ component 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 Probability of Switching

We first explore the determinants of major switching. As a reminder, the model suggests four factors that should matter: early-college grades, initial mismatch on preferences, and sensitivity to academic and preference mismatch. Of these, only grades are actually observable. We will also ask if certain characteristics of students and majors predict switching, as these might provide insight into what types of people and majors are most likely to be mismatched, or are most sensitive to mismatch. We run linear probability models of the form

$$switch_{im\tilde{m}} = X_i\beta_1 + \Phi_m\beta_2 + \beta_3 GPA_i$$

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. X_i includes personal char-

[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.

acteristics like race and gender, Φ_m includes major characteristics like competitiveness and gender makeup, and GPA_i is the student's early-college GPA.

Table 3 reports results for these regressions only on grades and personal characteristics. In column 1, women are about 5 percentage points more likely to switch than men, while blacks and Hispanics are more likely to switch than whites.[37] This suggests that women and minorities are more likely to be mismatched or have a higher sensitivity to being mismatched.[38]

Column 2 adds early-college GPA. As predicted by the model, lower grades predict switching majors; a one-point lower GPA (on a 4-point scale) leads to a 5.7 percentage point lower probability of switching, about the same effect size as gender. Column 3 provides evidence that females are more sensitive to low grades than males are; the coefficient on the interaction term is large, though not significant.[39] This is suggestive that women may have a higher α_x than men do. Column 4 finds no significant difference in how high- and low-test score students respond to grades.

It is also useful to look at what types of majors have the highest switch-out rates, as these are majors where more students find themselves mismatched. If most students prefer non-competitive majors, for example, then competitive majors will see high switch-out rates. Table 4 includes the same personal characteristics but now also adds major characteristics – the average SAT math score in the major ("competitiveness") and the male, black, Hispanic, and Asian percentages of the major.

The most striking findings from this table concern competitive majors. Students flee majors that are competitive. A one standard deviation higher competitiveness score for the major has twice the effect on switching probability as a one point lower GPA. This effect is not uniform, however. Column 2 shows us that it is primarily women who are leaving competitive majors: the effect of being in a competitive major on switching is more than twice as large for females as for males. This suggests that, on average, females prefer less competitive majors than males do, which is consistent with other evidence (Buser et al. 2014).

[37] Women and men are equally likely to report "no major" as their first major, so the gender gap in switching does not seem to be explained by differences in the timing of major choice.

[38] One might suspect that higher rates of switching for minorities reflect a lack of familiarity with college relative to whites. However, the racial gaps are of similar size when restricting to first-generation college students.

[39] A gender difference in sensitivity to grades would be consistent with evidence from Ost (2010).

Column 3 tells us that students with lower test scores (AFQT) are more likely to leave competitive majors, but this too differs by gender. In column 4, we see that it is only *women* with lower test scores – not men with lower test scores – who are more likely to leave competitive majors. The coefficients here imply that there is no effect of major competitiveness on men's switch-out probabilities, but moderate effects for high-score women and large effects for low-score women.[40] Even a high-score woman is more deterred by competitive majors than a low-score man.

Columns 1 and 2 tell us that other characteristics of majors – race and gender makeup – are also correlated with switch-out probability. Surprisingly, however, these effects do not seem to be different by the race and gender of the student. It may be that the race and gender makeup of the major is correlated with other factors we are not including here.[41]

In sum, grades, race, and gender are strong predictors of major switching, with women and blacks switching majors more often than men and whites. Gender and one point of GPA have about the same effect on the probability of switching. We point this out here so that we can compare it to the results for STEM in Section 5. The majors that people switch *out* of tend to be competitive majors, but this turns out to be only true for women, and particularly women with lower test scores.

4.2 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 are a signal of academic mismatch. 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

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

[40]Fischer (2016) also finds that females with lower test scores are the most sensitive to having high-quality peers in introductory science classes.

[41]We have also experimented with using the specificity of the major as a characteristic, which we find is not related to switch-out rates.

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

Table 5 has the results. As expected, grades are a significant predictor of distance: students with lower grades make larger switches. This is strong evidence that grades are a signal of academic mismatch that leads students to revise their beliefs about their own abilities. While gender and race were related to the probability of switching, they are mostly unrelated to the distance of switching, with the exception of Asians, for whom the sample size is small. Combined with the results from Table 3, this suggests that the gender gap in switching rates is due to mismatch on preferences (or sensitivity to that mismatch), not mismatch on abilities. If the gender gap in switching were due to academics, then it would show up here in Table 5, but it does not.

Columns 3 and 4 include some major characteristics. Interestingly, the more competitive the major – and competitive majors have high switch-out rates – the smaller the switch the student makes. This makes sense if students leaving competitive majors are fleeing the competitiveness itself, which is an m^θ characteristic, and not the mix of academic courses in those majors.

Figure 1 shows the distribution of early-college GPA for those who do not switch majors (solid line) and then for switchers, broken up into three terciles by the size of the switch. Those who do not switch and those who make small switches have the highest GPAs; these "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. These are students who discovered that they were badly mismatched academically with their initial major and responded by making a "major change".

To further establish that low grades signal academic mismatch, Table 6 looks at what happens to a student's GPA when she changes majors, and how the academic distance of that major switch relates to the change in GPA. Here we regress

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

The dependent variable is the change in GPA from before the switch to after the switch.[42] Column 1 tells us that when students switch majors, grades seem to improve, but the effect is small and insignificant. Recall from the model that some students may switch majors only because they are mismatched on preferences; in this case, we would not expect an increase in grades.

However, the model is clear that the larger the academic distance of the switch, the more grades should improve. Columns 2 and 3 confirm this. Larger switches are associated with larger improvements in GPA.[43]

Interestingly, in column 3, we see that how the m^{θ} characteristics of the major change has no effect on the change in GPA. Moving to a major that matches a student's preferences does not mean that the student will then perform better academically. Only when students switch to a major closer to their *abilities* do they see grade improvement.[44]

Also in column 3, the fact that including the change in SAT math does not alter the effect of the distance of switch is informative. One might have thought that the real key is whether the student moves to an "easier" major (one with lower SAT scores), rather than to a better match. However, here we see that the change in SAT math has no significant effect on the change in grades, while the distance of switch is the main driver. This supports our story that an improving match is what drives the grade improvement.[45]

Our results in this section are robust for our alternative measure of academic distance, as defined in Section 3. Appendix Tables 1 and 2 repeat Tables 5 and 6 for this alternative distance measure, and the results are similar to our main results.[46]

To summarize, low grades are a signal of academic mismatch. The lower a student's

[42]For non-switchers, it is the GPA in the last two years minus the GPA in the first two years.

[43]Some of this effect – lower grades lead to bigger moves, which lead to greater grade improvement – could actually be that lower grades cause students to work harder in order to improve their grades. In this case, we are overstating the causal effect of the distance of switch on grades. Even if we include early-college grades on the right hand side of these regressions, though, the effect of the distance of switch on grade improvement is still positive.

[44]In Expressions (3) and (4) in the model, we assumed that the student's disutility of mismatch is separable in the x and θ components. The findings here support that assumption and suggest no need for an interaction term.

[45]The results of Table 6 are similar if we exclude switchers who had near-perfect early GPAs (and thus could not see any grade improvement).

[46]Recall that the alternative distance measure is a binary indicator, rather than a continuous measure. The regressions in Appendix Tables 1 and 2 are Linear Probability Models.

grades, the larger a major switch she will make. And the larger a student's major switch, the more her grades improve after the switch.

4.3 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 cultural characteristics of the major (m^θ) change with major switches. Students should be moving to majors that better match their preferences, but we as researchers do not observe those preferences. Thus, the switching patterns we observe in the data will tell us something about students' preferences. Here our regressions – restricting to those who switched majors – are of the form

$$d_{ij}(m^\theta, \tilde{m}^\theta) = X_i\xi_1 + \xi_2 m_j^\theta + \xi_3 GPA_i$$

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

Table 7 gives the results, which are striking. The main takeaway from this table is that overwhelmingly, 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, Asians to Asian-heavy majors, and so on. The effect is strongest for women fleeing male-dominant majors.[47] The major-switching process appears to be a process by which students find their identity and preferred peer group, not just their best academic match, and it appears that students prefer a peer group that looks similar to them.

From Table 4, we know that women are much more likely to leave competitive majors than men are. Now, in column 1 of Table 7, we also see that females who switch majors move to much less competitive majors than males do. Not only are women leaving competitive majors, but they are also likely to choose a new major

[47]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 (Hoffmann and Oreopoulos (2009), Price (2010)).

that is less competitive. This seems to confirm that women's preferences s^θ include a distaste for competitive environments.[48]

These results highlight an advantage of our approach in studying major choice as a process. Women shy away from competitive majors, but much of this shows up not in their initial major choice, but in the switching decision. If, instead of studying the switching process, one only looked at the final major decision and found that women were unlikely to be in competitive majors, one would not be able to tell if this was because women disliked competition or because women could not handle the difficult academics. As we will see again in Section 5, many women who are well-matched academically and performing well in difficult majors are driven away by the culture of those majors.

Next, we look at how the course requirements of majors (m^x) change with major switches. The model tells us 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.

In Table 8, we run regressions similar to Table 7, but for the direction of change in academic characteristics when a student switches from major m to major $\tilde{m}$ Here we also interact GPA with the academic characteristic of the initial major. We expect that the GPA interaction terms will be positive, meaning GPA has a larger effect the more of that subject the initial major required.

The results here are consistent with the model's predictions. The coefficients on the interaction terms are all positive – suggesting that receiving higher grades in a given area leads a student to move toward that area – but the estimates are imprecise, and only the business interaction is significant. Recall that we do not actually observe which classes the grades a student received came from. Perhaps if we had that information, we would be able to estimate these effects more precisely.

To summarize our main results, grades, gender, and major characteristics are all

[48]An alternative explanation is that all students dislike competitive majors, but men tolerate it because they care more about future earnings (Zafar 2013). This is plausible, but the past literature on women's dislike of competitive situations suggests our interpretation is sound as well.

important for understanding major switching behavior. Low grades signal academic mismatch and lead to major switches – and the lower the grades, the larger the switch. When students switch majors, their grades improve – and the larger the switch, the larger the grade improvement. Women change majors more, and in particular they flee competitive and male-dominated majors at high rates. When students change majors, they seek out majors that match their own characteristics in terms of race and gender makeup. Clearly, both academic considerations and preferences are driving major switching.

5 Switching Out of STEM: Results

For our last set of results, we focus particularly on students switching out of STEM fields. In the model, one can think of STEM majors as occupying a particular range in both the academic (high science/engineering/math) and cultural (competitive, male-heavy, Asian-heavy) 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), Speer (2016)).

The gender gap in STEM fields grows from the beginning of college to the end of college. In our data, the STEM male-to-female ratio in initial major choice is about 2 to 1. In final major choice, the ratio is nearly 3 to 1. Because STEM fields have particular characteristics in both the x and θ components, the key question is why women are so likely to leave – is it because of the academics, because of the men, because of the competitiveness, or something else? Our framework allows us to investigate this question by looking at where they go when they leave STEM.

First, Table 9 investigates the determinants of switching out of STEM.[49] Both low grades and being female predict switching, but the gender effect is almost twice as large as the grade effect. For the overall switching results (Table 3), gender and GPA had about the same effect. Here, gender is the dominant factor.[50] None of the large

[49]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.

[50]In the raw data, among those who start a STEM major, women are 76% more likely than men to leave. In fact, while only 38% of those who *start* STEM majors are women, 52% of those who *leave*

gender gap in switching is explained by grades. There is also no evidence that women are more sensitive to grades in making the decision to leave STEM fields. Women are fleeing STEM at much higher rates than men are, and it is not because they cannot perform well academically.

Next, Table 10 looks at the academic distance moved by those who switch out of STEM. Women are more likely to switch out of STEM, but it is actually the male switchers who make larger moves when they do switch. This is more evidence that the women who leave STEM are not leaving because they do not like science or cannot perform well in science fields. Low grades also lead students to switch to further-away majors, although the effect is imprecisely measured. The interaction term hints that women may respond more strongly to grades in terms of where they switch.

What effect does this have on grades? Appendix Table 3 shows that leaving STEM leads to grade improvement, and the larger the switch out, the larger the improvement in grades. The effects of switching and distance here are larger than the overall results in Table 6. It seems clear that low grades are signaling academic mismatch in STEM fields.

Finally, Table 11 looks at the direction of change in major cultural characteristics (m^{θ}) when students leave STEM fields. The most dramatic result in this table is in column 2: when women leave STEM, they are fleeing male-dominated majors to find a major with more females, and the effect is large. There are few significant coefficients in the other columns, which mostly reflects small sample sizes.

The other result of interest here is in column 1. The constant term tells us that the average STEM switcher is finding a less competitive major, and the gender coefficient – though not significant – tells us that this effect is almost twice as large for women. Most students leaving STEM are looking for less competition in their new major, and this is especially true for women.[51]

Putting the results of Tables 9-11 together, we see that women flee STEM at much higher rates than men, but this is not because they cannot make the grades, and it is not because they do not like science- or math-heavy fields. Instead, it seems to be because STEM fields are competitive and dominated by males. When women leave STEM, they

STEM majors are women. Women's exit rate from STEM is 51%, while men's is 29%.

[51]The results of Table 11 are qualitatively unchanged if we exclude those who switch to nursing, although the gender coefficient in column 2 (for the male share) is reduced to -0.25.

look for majors that are similar academically but have dramatically different gender makeup and lower levels of competitiveness.

Appendix Table 4 shows the destinations of students who switch out of STEM separately by gender, with majors sorted by their academic distance to STEM fields. Given our results, it is no surprise that students who switch to the two closest majors to STEM – nursing and other medical/health services – are overwhelmingly female. These are both similar to STEM in academic content but very different in gender makeup.[52] A move from STEM to nursing is a small move in x terms but a huge move in θ terms. On the other hand, most STEM students who switch to business – a large academic change but a less dramatic change in gender makeup – are male.[53]

Figure 2 visualizes some of these results, looking at GPA distributions for initial STEM majors who do not switch majors, those who switch to nursing (a small academic change), those who switch to psychology (a medium change), and those who switch to education (a large change). The non-switchers have the highest GPAs, followed by the nurses. Clearly, women leaving STEM for nursing are not doing so because they cannot handle the academics. Those switching to education – the largest move – have the lowest GPAs of all. This figure includes both men and women, but it looks almost identical when restricted to women.[54]

Two things must be said about the STEM results. First, the determinants of switching should not be confused with the determinants of the overall gender gap in STEM. While the gender gap in switching is mostly driven by preferences, Speer (2016) shows that a large portion of the overall gap in STEM majors is related to pre-college abilities, as measured by test scores. This is perfectly consistent with our results and our model. Many women are not well-prepared for a science major entering college, and they therefore do not choose a science major. Many other women, though, are

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

[53]Business is actually the most common destination for both male and female STEM switchers, because it is a large major, 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.

[54]Some nursing programs may use a GPA cutoff for admission, which would exclude some students who wish to switch into nursing from doing so (and could explain the large "hump" near a 3.0 GPA in Figure 2). Our investigation into this reveals that while some programs do use a hard cutoff, standards are not consistent across schools, so while this may affect the results, it is not possible for us to account for it.

perfectly competent in science but then discover they do not like the culture of a science major, leading them to switch out.

This leads to the second point: colleges and policymakers seeking to attract and retain women to STEM fields may face an uphill battle. Initiatives that help women be better prepared for science fields can help, but even well-prepared women who get good grades are leaving STEM majors. Our results suggest that as long as STEM fields are mostly male, women may still be unlikely to stay.

6 Adding Major Earnings to the Model

As we have said, our model is meant to guide our thinking and to help us interpret the empirical results. It is intentionally parsimonious, and there is no explicit mention of a major's earnings return or average earnings. This aspect is not completely absent, 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 are strongly correlated with average earnings. In this brief section, we discuss how one could include major earnings more explicitly in the student's decision and why we chose the simpler formulation laid out in Section 2.

Suppose now that a major is a vector m with three components: academics m^x, nonacademic characteristics m^θ, and average earnings m^E. A student is still two components, s^x and s^θ, as described before. Now the disutility of being in major m is

$$\alpha_x D(m^x, s^x) + \alpha_\theta D(m^\theta, s^\theta) - \alpha_E m^E$$

where α_E represents how much the student cares about major earnings. We can now interpret the academic (x) match as representing a student's expected variation around the average earnings m^E if she stays in that major. For instance, if the major has high average earnings but the student is poorly-matched on abilities, she will likely earn below that average if she completes the major.[55] This has an intuitive appeal. A

[55] One issue in this formulation is to what degree m^E is known by students upon college entry. Wiswall and Zafar (2015) show that students make considerable errors before being given information about average earnings. The patterns in our data suggest that this point is not terribly important. While their paper shows that students initially believe that economics majors earn more than engineering majors (the opposite is true), far more students switch from engineering to economics than the

poorly matched engineering student may still earn more than a well-matched history major, and thus she may want to stay in engineering rather than switch to history.

The student's switching condition is similar to equation (5) above, except that a student must also consider the change in average earnings when switching majors. This would have two effects on the model's conclusions. First, some switches which were profitable in our model (improvements in match) may no longer be so. Some students who are mismatched with their major may choose not to switch. Second, some students might switch to majors which are worse matches, which is impossible in the simpler model.

Note that our model in Section 2 is a special case of this expanded model, when α_E is negligible. If students do not consider the average earnings of the major strongly in their decisions, our predictions will still hold, and unless α_E is large, the conclusions will be similar.

We preferred the simpler model in our main analysis for three main reasons. First, prior literature suggests a limited role for major earnings in students' decisions. Arcidiacono (2004) concludes that, "Differences in monetary returns explain little of the ability sorting across majors", but rather sorting is mostly based on preferences. Second, some of the m^θ characteristics we use in our analysis – average test scores in the major, percent male, and percent Asian – are highly correlated with average earnings in the major.[56] Thus, information about majors' average earnings is already included to some degree in the major characteristics we use.

Finally, the patterns we observe in the data suggest that average earnings is not a major driver of student switching. There is no discernible movement toward higher-paying majors; if anything, the opposite is true. About 56% of major switches are to majors with lower average earnings. Some students are likely motivated by moving to a higher-earning major, but it is not the prevailing pattern. The characteristics that are most correlated with major earnings – male share, Asian share, and SAT math scores – are characteristics that many students flee when changing majors. Similarly, many more students switch out of STEM majors (which are generally high-paying) than

other way around – the opposite of what would happen if students' learning about earnings induced switches.

[56]The correlations between average earnings and male share, Asian share, and SAT math scores are 0.76, 0.86, and 0.63, respectively.

switch in. It is not plausible that students who switch are doing so because they prefer lower-earning majors. It is more plausible that they dislike characteristics correlated with high earnings.

We suspect – and this is worthy of future research – that a major's average earnings play two primary roles in the results we have presented. First, they influence the initial major decision, before students learn about their abilities and about what kind of major characteristics they prefer. Second, earnings considerations prevent some match-improving switches from being made. It is likely, for example, that some poorly-matched students stay in STEM fields because of earnings considerations, so that the flow of students out of STEM would be even greater without them. Taken as a whole, however, our results generally confirm the predictions of the simpler model and suggest that it is not necessary to include earnings to generate key insights into major switching behavior.

7 Conclusion

We have provided the first comprehensive analysis of major switching among college students, studying college major choice as a two-stage matching process between student and major. Major switching is common, with more than 40% of graduates finishing in a different major than the one they started in. Switches occur for two reasons: academic mismatch and preference mismatch. Low grades signal academic mismatch and lead students to look for a new major that better matches their abilities. Even if grades are good, though, students may find themselves mismatched on nonacademic characteristics – such as competitiveness or gender makeup – which can also lead to switches. No single factor can explain all students' major switching decisions.

Not all major changes are created equal. Some students make "major changes" – switching from one major to a major with radically different academic characteristics. Other students switch to majors that are similar in academic characteristics but very different in culture. 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.

When students switch majors, their grades improve - and the larger the switch, the greater the improvement. Women are more likely to switch majors than men are, and when they do switch, they seek out less competitive, less male-dominated majors. Overwhelmingly, when students switch majors, they are drawn to majors that "look like them". Major switching is partly about finding your preferred peer group, not just your academic match.

We have also provided a detailed analysis of those who switch out of STEM majors. Women are much more likely than men to leave STEM, but they are not fleeing science; rather, they are fleeing competitive and 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.

Colleges and policymakers seeking to influence students' major choices – particularly those wanting to attract more women to STEM fields – must be aware of both the academic and nonacademic motivations. Preparing women better for difficult fields can help them be better-matched academically with those fields when they arrive in college, making them more likely to stay. However, there are limits to the effectiveness of just improving the academic preparation of women in science. Many well-prepared women who arrive in STEM fields and enjoy science but dislike the male-dominated culture will still be unlikely to stay. As long as STEM majors are so disproportionately male, schools will likely have difficulty in retaining these women.

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Tables and Figures

Table 1

Summary Statistics

	n	Mean	St. Dev.	Min	Max
Female	2259	0.57	0.50	0	1
Black	2259	0.17	0.38	0	1
Hispanic	2259	0.13	0.34	0	1
Asian	2259	0.04	0.19	0	1
Early GPA	2248	3.12	0.55	0.00	4.00
Late GPA	2134	3.25	0.46	0.85	4.00
Change in GPA	2134	0.13	0.49	-2.25	3.64
AFQT	1954	0.25	0.93	-2.33	1.49
Major switch	2259	0.42	0.49	0	1
First major STEM	2259	0.24	0.43	0	1
Switch out of STEM	536	0.41	0.49	0	1
Among major switchers (in standard deviations):					
SAT math change	768	-0.14	1.36	-3.50	3.62
Male pct change	952	-0.08	1.28	-3.73	3.23
White pct change	952	0.11	1.35	-4.10	3.99
Black pct change	952	0.04	1.35	-4.42	4.08
Hispanic pct change	952	0.13	1.42	-3.95	4.08
Asian pct change	952	-0.15	1.26	-3.59	3.81

Note: Early GPA is GPA before the major switch, and late GPA is GPA after the major switch. For students who do not switch majors, early and late are the first two and last two years of college, respectively. SAT math is the average SAT math score in the major. All variables in the bottom panel (SAT math, male percentage, etc.) are measured in standard deviations.

Table 2
Major Characteristics, in Standard Deviations

	Course Measures						Nonacademic Characteristics				
Major	Math	Humanities	Business	Sci/Engin	SocSci	Educ	SAT math	% Male	% Black	% Asian	% White
Mathematics	6.09	-0.04	-0.54	0.03	-0.51	0.17	1.67	0.68	-1.26	0.96	-0.21
Engineering	2.12	-0.79	-0.53	2.97	-0.94	-0.45	2.20	2.04	-1.35	2.14	-1.62
Computer sci	1.71	-0.45	0.02	-0.13	-0.61	-0.45	1.39	1.94	-0.08	2.62	-2.31
Physical Sci	0.76	-0.54	-0.67	2.57	-0.27	-0.07	–	0.80	-1.15	0.66	0.15
Biological Sci	0.32	-0.16	-0.69	2.62	-0.54	-0.31	1.24	-0.16	-0.22	1.17	-0.89
Economics	0.28	0.24	0.31	-0.42	1.71	-0.43	1.83	1.30	-0.67	0.89	-0.52
Interdisc/General	-0.02	-0.09	-0.56	0.41	-0.33	–	0.03	-0.31	0.95	0.26	-0.68
Architecture	-0.11	-0.74	-0.70	-0.23	-0.79	-0.48	–	0.78	-1.30	0.23	-0.23
Education	-0.16	-0.35	-0.69	-0.37	-0.40	3.11	-1.39	-1.28	-1.11	-1.19	1.82
Business	-0.16	-0.56	1.82	-0.55	-0.38	-0.42	-0.38	0.28	0.44	-0.12	-0.04
Agriculture	-0.19	-0.89	0.26	0.48	-0.64	-0.40	0.33	0.43	-1.89	-1.01	2.18
Family sci	-0.28	-0.60	-0.40	-0.30	-0.21	0.29	-1.05	-1.75	2.31	-0.67	-0.24
Psychology	-0.36	0.11	-0.59	-0.31	2.06	-0.22	-0.15	-1.14	1.17	-0.51	-0.15
Foreign Lang	-0.38	3.28	-0.56	-0.39	-0.11	0.07	0.14	-0.85	-1.73	-0.55	-0.44
Communications	-0.45	0.73	-0.41	-0.45	0.30	-0.35	-0.69	-0.20	0.25	-0.75	0.74
Other soc sci	-0.45	-0.02	-0.62	-0.37	1.80	-0.23	-0.31	-0.48	1.24	-0.48	-0.90
Other med/health	-0.45	-0.83	-0.64	0.38	-0.89	-0.26	-0.64	-0.12	0.42	0.30	-0.37
Area studies	-0.48	1.27	-0.60	-0.42	1.60	-0.32	0.36	-0.74	1.16	-0.15	-0.49
English/Lit	-0.50	3.81	-0.67	-0.44	-0.11	-0.12	0.15	-0.64	-0.23	-0.50	-0.91
Political Sci	-0.53	0.66	-0.60	-0.43	2.63	-0.39	0.18	0.28	-0.23	-0.45	0.58
History	-0.58	0.58	-0.65	-0.44	2.40	-0.06	0.67	0.77	-1.46	-0.96	0.31
Arts/Art History	-0.62	1.57	-0.68	-0.39	-0.58	-0.17	0.59	-0.66	-0.83	-0.27	1.66
Law/Public Admin	-0.65	-0.44	-0.14	-0.60	0.06	-0.45	–	0.52	2.73	-1.07	0.42
Philosophy/Relig	-0.67	2.00	-0.69	-0.46	0.03	-0.18	0.94	1.19	-1.60	-0.86	-0.51
Nursing	-0.84	-0.82	-0.70	-0.01	-0.90	-0.42	-1.39	-1.80	0.07	0.16	1.63

Note: All measures 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 is the average SAT math score in the major, also from the Baccaluareate and Beyond. The gender and racial percentages are calculated from the American Community Survey 2009-2014, using graduates from 2003 to 2008.

Table 3
Major Switching: Gender, Race, and Grades

	(1) Major Switch	(2) Major Switch	(3) Major Switch	(4) Major Switch
Female	0.049**	0.054**	0.037	0.037
	(0.023)	(0.023)	(0.024)	(0.024)
Early GPA		-0.057***	-0.023	-0.018
		(0.021)	(0.033)	(0.034)
Female*GPA			-0.063	-0.065
			(0.043)	(0.043)
AFQT	0.002	0.008	-0.027	-0.027
	(0.013)	(0.014)	(0.020)	(0.020)
Female*AFQT			0.063**	0.063**
			(0.026)	(0.026)
AFQT*GPA				-0.013
				(0.023)
Black	0.105***	0.097***	0.098***	0.099***
	(0.033)	(0.033)	(0.033)	(0.033)
Hispanic	0.062*	0.065*	0.065*	0.063*
	(0.035)	(0.035)	(0.035)	(0.036)
Asian	0.013	0.015	0.015	0.015
	(0.057)	(0.058)	(0.058)	(0.058)
Constant	0.371***	0.369***	0.383***	0.384***
	(0.020)	(0.020)	(0.021)	(0.021)
Observations	1,954	1,945	1,945	1,945
R-squared	0.010	0.014	0.017	0.017

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: The dependent variable is a dummy for switching majors. Early GPA is GPA before the major switch. For students who do not switch majors, early GPA is the first two years of college. GPA is de-meaned so that the main effect is the effect at the mean GPA. SAT math is the average SAT math score in the major, in standard deviations. AFQT is in standard deviations.

Table 4
Major Switching: First Major Characteristics

	(1) Major Switch	(2) Major Switch	(3) Major Switch	(4) Major Switch
Personal Characteristics:				
Female	0.031	0.029	0.061**	0.067***
	(0.025)	(0.025)	(0.024)	(0.026)
Black	0.099***	0.092***	0.086**	0.087**
	(0.034)	(0.034)	(0.034)	(0.034)
Hispanic	0.055	0.053	0.051	0.053
	(0.037)	(0.037)	(0.037)	(0.037)
Asian	-0.013	-0.033	-0.022	-0.018
	(0.059)	(0.062)	(0.060)	(0.060)
AFQT	-0.009	-0.007	-0.006	-0.020
	(0.015)	(0.015)	(0.015)	(0.021)
Female*AFQT				0.015
				(0.027)
Early GPA	-0.065***	-0.065***	-0.063***	-0.064***
	(0.022)	(0.022)	(0.022)	(0.022)
Major Characteristics:				
SAT math	0.130***	0.062*	0.006	-0.004
	(0.027)	(0.037)	(0.018)	(0.019)
Female*SAT math		0.088**	0.080***	0.095***
		(0.037)	(0.024)	(0.026)
AFQT*SAT math			-0.035***	-0.005
			(0.013)	(0.019)
Female*AFQT*SAT math				-0.055**
				(0.026)
Male pct	-0.103***	-0.100***		
	(0.019)	(0.030)		
Female*Male pct		-0.004		
		(0.038)		
Black pct	0.046**	0.021		
	(0.023)	(0.025)		
Black*Black pct		0.035		
		(0.042)		
Hispanic pct	-0.053**	-0.038		
	(0.023)	(0.024)		
Hispanic*Hispanic pct		-0.049		
		(0.041)		
Asian pct	-0.017	0.003		
	(0.025)	(0.026)		
Asian*Asian pct		0.065		
		(0.057)		
Constant	0.368***	0.379***	0.378***	0.374***
	(0.021)	(0.022)	(0.022)	(0.022)
Observations	1,802	1,802	1,802	1,802
R-squared	0.038	0.046	0.032	0.034

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: The dependent variable is a dummy for switching majors. Early GPA is GPA before the major switch. For students who do not switch majors, early GPA is the first two years of college. GPA is de-meaned so that the main effect is the effect at the mean GPA. AFQT is in standard deviations. SAT math is the average SAT math score in the major, in standard deviations. The gender and race percentages are the makeup of the major as calculated in the ACS, in standard deviations.

Table 5
Academic Distance of Switching

	(1) Distance of switch	(2) Distance of switch	(3) Distance of switch	(4) Distance of switch
Female	-0.113	-0.106	-0.149*	-0.107
	(0.083)	(0.083)	(0.089)	(0.089)
Early GPA	-0.201***	-0.283**	-0.188**	-0.169**
	(0.072)	(0.116)	(0.075)	(0.073)
Female*GPA		0.147		
		(0.143)		
Black	-0.116	-0.117	-0.106	-0.073
	(0.112)	(0.112)	(0.117)	(0.114)
Hispanic	-0.171	-0.168	-0.139	-0.140
	(0.124)	(0.124)	(0.134)	(0.130)
Asian	-0.444**	-0.454**	-0.470**	-0.473**
	(0.211)	(0.211)	(0.230)	(0.224)
AFQT	-0.107**	-0.108**	-0.133**	-0.094*
	(0.049)	(0.049)	(0.053)	(0.052)
AFQT*GPA		-0.028		
		(0.083)		
SAT math			-0.046	-0.486***
			(0.068)	(0.092)
Female*SAT math			-0.127	
			(0.090)	
AFQT*SAT math			0.047	
			(0.048)	
Male pct				0.001
				(0.068)
Black pct				-0.403***
				(0.081)
Hispanic pct				0.045
				(0.078)
Asian pct				0.351***
				(0.088)
Constant	0.425***	0.424***	0.460***	0.415***
	(0.075)	(0.076)	(0.082)	(0.078)
Observations	830	830	745	745
R-squared	0.027	0.028	0.047	0.107

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Note: The sample is all major switchers. The dependent variable is the distance of major switch. Early GPA is GPA before the major switch. For students who do not switch majors, early GPA is the first two years of college. GPA is de-meaned so that the main effect is the effect at the mean GPA. AFQT is in standard deviations. SAT math is the average SAT math score in the major, in standard deviations. The gender and race percentages are the makeup of the major as calculated in the ACS, in standard deviations.

Table 6
Change in GPA with Major Switches

	(1) GPA Change	(2) GPA Change	(3) GPA Change
Major switch	0.015		
	(0.023)		
x distance of switch		0.039**	0.033*
		(0.016)	(0.018)
Female	0.044*	0.095**	0.049
	(0.023)	(0.039)	(0.043)
Black	-0.082**	-0.081	-0.088
	(0.033)	(0.052)	(0.057)
Hispanic	-0.090**	-0.105*	-0.083
	(0.036)	(0.058)	(0.066)
Asian	-0.051	0.025	-0.002
	(0.057)	(0.097)	(0.110)
AFQT	-0.032**	-0.028	-0.036
	(0.013)	(0.022)	(0.025)
SAT math change			-0.003
			(0.030)
Male pct change			-0.032
			(0.024)
Black pct change			-0.029
			(0.027)
Hispanic pct change			0.014
			(0.024)
Asian pct change			-0.005
			(0.028)
Constant	0.123***	0.094***	0.133***
	(0.022)	(0.036)	(0.041)
Observations	1,856	799	644
R-squared	0.009	0.021	0.025

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: The sample in columns 2 and 3 is all major switchers. The sample in column 1 is the full sample. The dependent variable is late GPA minus early GPA. Early GPA is GPA before the major switch, and late GPA is GPA after the switch. For students who do not switch majors, early GPA is the first two years of college and late GPA is the last two years of college. Major distance is measured as described in Section 3. AFQT is in standard deviations. SAT math is the average SAT math score in the major, in standard deviations. The gender and race percentages are the makeup of the major as calculated in the ACS, in standard deviations.

Table 7
Direction of Switching (Cultural Characteristics)

	Dependent Variables: Change in Major Characteristic From Old to New Major					
	(1)	(2)	(3)	(4)	(5)	(6)
	SAT math	Male pct	White pct	Black pct	Hispanic pct	Asian pct
Female	-0.586***	-0.591***	0.284***	0.170**	0.124	-0.359***
	(0.075)	(0.067)	(0.068)	(0.072)	(0.076)	(0.062)
Black	0.116	-0.035	-0.168*	0.230**	0.221**	0.028
	(0.099)	(0.087)	(0.091)	(0.096)	(0.102)	(0.082)
Hispanic	0.188	0.109	-0.256**	0.091	0.166	0.168*
	(0.117)	(0.098)	(0.102)	(0.107)	(0.114)	(0.092)
Asian	0.315	0.251	-0.310*	-0.134	-0.111	0.361**
	(0.197)	(0.165)	(0.173)	(0.181)	(0.193)	(0.156)
Early GPA	0.103	0.025	-0.061	-0.042	-0.074	0.094*
	(0.064)	(0.056)	(0.059)	(0.062)	(0.066)	(0.053)
AFQT	0.105**	0.012	-0.001	-0.076*	0.001	0.023
	(0.045)	(0.038)	(0.040)	(0.042)	(0.045)	(0.036)
First major's value of	-1.062***	-1.002***	-1.006***	-0.964***	-0.970***	-0.974***
dependent variable	(0.039)	(0.035)	(0.034)	(0.037)	(0.038)	(0.031)
Constant	0.254***	0.220***	0.006	-0.181***	-0.102	0.076
	(0.068)	(0.059)	(0.061)	(0.065)	(0.069)	(0.055)
Observations	670	830	830	830	830	830
R-squared	0.538	0.509	0.521	0.455	0.446	0.548

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 characteristic, all measured in standard deviations. Early GPA is GPA before the major switch. AFQT is in standard deviations. SAT math is the average SAT math score in the major, in standard deviations. The gender and race percentages are the makeup of the major as calculated in the ACS, in standard deviations.

Table 8
Direction of Switching (Academic Characteristics)

	Dependent Variables: Change in Major Characteristic From Old to New Major					
	(1)	(2)	(3)	(4)	(5)	(6)
	Math	Humanities	Sci/Engin	Edu	Business	Soc Sci
Female	-0.325***	-0.014	-0.120*	0.347***	-0.231***	-0.049
	(0.070)	(0.075)	(0.065)	(0.073)	(0.063)	(0.079)
Black	0.032	0.079	-0.118	-0.188*	0.014	0.167
	(0.093)	(0.101)	(0.087)	(0.099)	(0.084)	(0.106)
Hispanic	0.068	-0.075	0.132	-0.234**	-0.070	-0.035
	(0.104)	(0.113)	(0.097)	(0.110)	(0.093)	(0.118)
Asian	0.059	-0.190	0.113	-0.332*	0.033	0.107
	(0.176)	(0.191)	(0.165)	(0.187)	(0.158)	(0.200)
AFQT	-0.021	0.087*	0.055	-0.106**	-0.067*	0.019
	(0.041)	(0.045)	(0.038)	(0.044)	(0.037)	(0.046)
Early GPA	0.141**	0.072	0.077	-0.005	-0.078	-0.020
	(0.060)	(0.066)	(0.056)	(0.064)	(0.057)	(0.069)
First major's value of	-0.872***	-0.871***	-0.919***	-1.087***	-1.104***	-0.978***
dependent variable	(0.036)	(0.036)	(0.030)	(0.040)	(0.040)	(0.037)
Early GPA*First value	0.058	0.092	0.034	0.046	0.150**	0.029
	(0.060)	(0.064)	(0.053)	(0.070)	(0.068)	(0.056)
Constant	0.121*	0.093	0.030	-0.024	-0.039	0.158**
	(0.062)	(0.068)	(0.058)	(0.066)	(0.056)	(0.071)
Observations	830	830	830	830	830	830
R-squared	0.420	0.426	0.541	0.502	0.513	0.469

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 characteristic, all measured in standard deviations. Early GPA is GPA before the major switch. GPA is de-meaned so that the main effect is the effect at the mean GPA. AFQT is in standard deviations. SAT math is the average SAT math score in the major, in standard deviations. The gender and race percentages are the makeup of the major as calculated in the ACS, in standard deviations.

Table 9

Switching out of STEM

	(1)	(2)	(3)	(4)
	Leave STEM	Leave STEM	Leave STEM	Leave STEM
Female	0.202***	0.208***	0.271***	0.273***
	(0.046)	(0.046)	(0.051)	(0.051)
Early GPA		-0.111***	-0.117**	-0.061
		(0.041)	(0.053)	(0.059)
Female*GPA			0.034	-0.003
			(0.083)	(0.084)
AFQT	-0.078***	-0.061**	-0.005	-0.006
	(0.029)	(0.030)	(0.037)	(0.037)
Female*AFQT			-0.144**	-0.138**
			(0.056)	(0.056)
AFQT*GPA				-0.097**
				(0.047)
Black	0.030	0.013	0.016	0.026
	(0.069)	(0.069)	(0.068)	(0.068)
Hispanic	0.106	0.103	0.107	0.110
	(0.071)	(0.071)	(0.071)	(0.071)
Asian	0.065	0.060	0.071	0.071
	(0.098)	(0.097)	(0.097)	(0.096)
Constant	0.338***	0.337***	0.304***	0.315***
	(0.039)	(0.040)	(0.041)	(0.042)
Observations	454	453	453	453
R-squared	0.079	0.094	0.108	0.117

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: The sample is all those whose first major was in STEM. The dependent variable is a dummy for switching out of STEM. Early GPA is GPA before the major switch. For students who do not switch majors, early GPA is the first two years of college. GPA is de-meaned so that the main effect is the effect at the mean GPA. AFQT is in standard deviations.

Table 10
Academic Distance of Switching, for STEM Switchers

	(1)	(2)	(3)	(4)
	Dist. of switch	Dist. of switch	Dist. of switch	Dist. of switch
Female	-0.302*	-0.328*	0.167	-0.387**
	(0.179)	(0.179)	(0.418)	(0.187)
Early GPA	-0.234	-0.118	-0.261	-0.226
	(0.160)	(0.240)	(0.173)	(0.146)
Female*GPA		-0.393		
		(0.315)		
Black	-0.168	-0.190	-0.226	-0.117
	(0.239)	(0.239)	(0.248)	(0.215)
Hispanic	-0.328	-0.387	-0.240	-0.270
	(0.253)	(0.256)	(0.266)	(0.229)
Asian	-0.593*	-0.556	-0.827**	-0.574*
	(0.353)	(0.353)	(0.403)	(0.347)
AFQT	0.102	0.124	0.009	-0.031
	(0.112)	(0.113)	(0.288)	(0.106)
AFQT*GPA		0.205		
		(0.204)		
SAT math			0.475**	-0.063
			(0.232)	(0.390)
Female*SAT math			-0.342	
			(0.295)	
AFQT*SAT math			0.075	
			(0.196)	
Male pct				-0.242**
				(0.105)
Black pct				-1.072**
				(0.415)
Hispanic pct				0.915**
				(0.444)
Constant	0.883***	0.885***	0.228	1.515***
	(0.162)	(0.162)	(0.369)	(0.272)
Observations	182	182	156	156
R-squared	0.064	0.078	0.118	0.353

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 variable is the distance of major switch. Early GPA is GPA before the major switch. For students who do not switch majors, early GPA is the first two years of college. GPA is de-meaned so that the main effect is the effect at the mean GPA. AFQT is in standard deviations. SAT math is the average SAT math score in the major, in standard deviations. The gender and race percentages are the makeup of the major as calculated in the ACS, in standard deviations.

Table 11
Direction of Switching, for STEM Switchers (Cultural Characteristics)

	Dependent Variables: Change in Major Characteristic From Old to New Major					
	(1)	(2)	(3)	(4)	(5)	(6)
	SAT math	Male pct	White pct	Black pct	Hispanic pct	Asian pct
Female	-0.173	-0.375***	0.013	-0.022	-0.087	-0.006
	(0.132)	(0.128)	(0.121)	(0.152)	(0.155)	(0.080)
Black	-0.011	-0.091	-0.024	0.049	0.142	-0.029
	(0.167)	(0.156)	(0.158)	(0.199)	(0.207)	(0.103)
Hispanic	0.307*	0.200	-0.212	0.029	0.324	0.111
	(0.177)	(0.164)	(0.165)	(0.208)	(0.217)	(0.108)
Asian	0.064	-0.108	0.086	-0.199	0.093	-0.044
	(0.270)	(0.231)	(0.233)	(0.294)	(0.309)	(0.152)
Early GPA	-0.033	-0.168	-0.128	0.131	0.128	0.055
	(0.112)	(0.104)	(0.105)	(0.132)	(0.138)	(0.068)
AFQT	0.190**	0.054	0.069	-0.121	-0.077	-0.015
	(0.078)	(0.075)	(0.075)	(0.093)	(0.097)	(0.049)
First major's value of	-1.047***	-0.981***	-0.951***	-0.834***	-0.927***	-0.978***
dependent variable	(0.092)	(0.066)	(0.074)	(0.124)	(0.178)	(0.052)
Constant	-0.239	-0.140	0.237*	0.292*	0.269	-0.327***
	(0.169)	(0.134)	(0.142)	(0.150)	(0.210)	(0.108)
Observations	145	185	185	185	185	185
R-squared	0.522	0.592	0.504	0.222	0.159	0.700

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 characteristic, all measured in standard deviations. Early GPA is GPA before the major switch. AFQT is in standard deviations. SAT math is the average SAT math score in the major, in standard deviations. The gender and race percentages are the makeup of the major as calculated in the ACS, in standard deviations.

Figure 1:

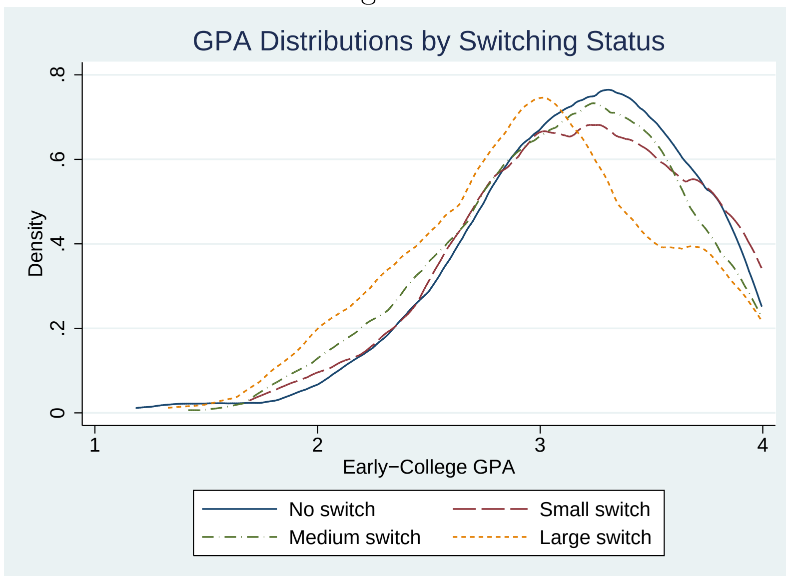
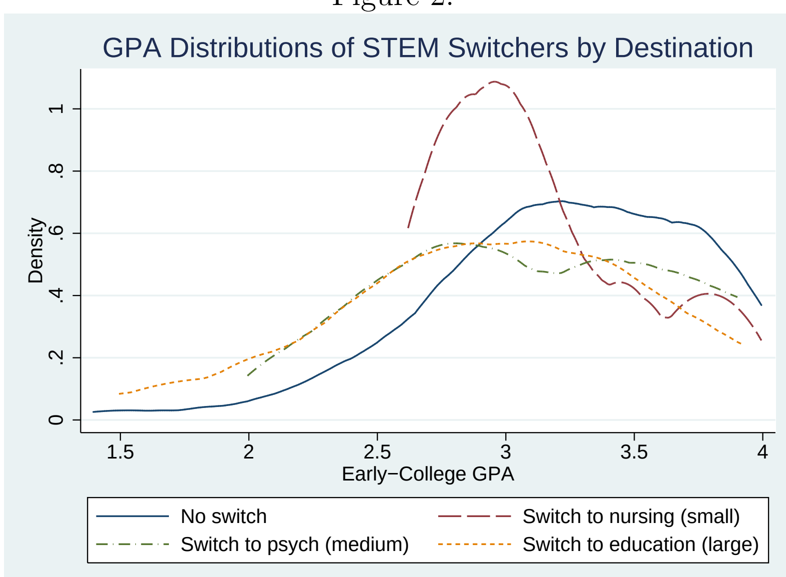


Figure 2:



Appendix Table 1
Academic Distance of Switching, Alternative Distance Measure

	(1) Distance of switch	(2) Distance of switch	(3) Distance of switch	(4) Distance of switch
Female	-0.041	-0.040	-0.063**	-0.029
	(0.029)	(0.030)	(0.031)	(0.032)
Early GPA	-0.048*	-0.064	-0.046*	-0.040
	(0.026)	(0.041)	(0.026)	(0.026)
Female*GPA		0.040		
		(0.051)		
Black	0.002	0.003	0.015	0.005
	(0.040)	(0.040)	(0.041)	(0.041)
Hispanic	-0.027	-0.026	0.003	-0.001
	(0.044)	(0.044)	(0.047)	(0.047)
Asian	-0.101	-0.103	-0.094	-0.113
	(0.075)	(0.075)	(0.081)	(0.080)
AFQT	-0.040**	-0.042**	-0.036*	-0.024
	(0.017)	(0.017)	(0.019)	(0.019)
AFQT*GPA		-0.026		
		(0.030)		
SAT math			0.010	-0.129***
			(0.024)	(0.033)
Female*SAT Math			-0.058*	
			(0.032)	
AFQT*SAT math			-0.004	
			(0.017)	
Male pct				0.092***
				(0.025)
Black pct				-0.013
				(0.029)
Hispanic pct				-0.010
				(0.028)
Asian pct				0.044
				(0.032)
Constant	0.820***	0.822***	0.830***	0.827***
	(0.027)	(0.027)	(0.029)	(0.028)
Observations	830	830	745	745
R-squared	0.020	0.022	0.030	0.060

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: The sample is all major switchers. The dependent variable is the distance of major switch, as measured by a dummy indicating whether the predominant course category of the major changed. Early GPA is GPA before the major switch. For students who do not switch majors, early GPA is the first two years of college. GPA is de-meaned so that the main effect is the effect at the mean GPA. AFQT is in standard deviations. SAT math is the average SAT math score in the major, in standard deviations. The gender and race percentages are the makeup of the major as calculated in the ACS, in standard deviations.

Appendix Table 2
Change in GPA with Major Switches, Alternative Distance Measure

	(1) GPA Change	(2) GPA Change	(3) GPA Change
Major switch	0.015		
	(0.023)		
Distance of switch		0.084*	0.080
		(0.045)	(0.052)
Female	0.044*	0.093**	0.048
	(0.023)	(0.039)	(0.043)
Black	-0.082**	-0.085	-0.091
	(0.033)	(0.052)	(0.057)
Hispanic	-0.090**	-0.109*	-0.088
	(0.036)	(0.058)	(0.066)
Asian	-0.051	0.017	-0.008
	(0.057)	(0.097)	(0.110)
AFQT	-0.032**	-0.030	-0.038
	(0.013)	(0.022)	(0.025)
SAT math change			-0.005
			(0.030)
Male pct change			-0.029
			(0.024)
Black pct change			-0.026
			(0.027)
Hispanic pct change			0.013
			(0.024)
Asian pct change			-0.006
			(0.028)
Constant	0.123***	0.043	0.083
	(0.022)	(0.051)	(0.060)
Observations	1,856	799	644
R-squared	0.009	0.018	0.023

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: The sample in columns 2 and 3 is all major switchers. The sample in column 1 is the full sample. The dependent variable is late GPA minus early GPA. Early GPA is GPA before the major switch, and late GPA is GPA after the switch. For students who do not switch majors, early GPA is the first two years of college and late GPA is the last two years of college. Major distance is measured by a dummy indicating whether the predominant course category of the major changed. AFQT is in standard deviations. SAT math is the average SAT math score in the major, in standard deviations. The gender and race percentages are the makeup of the major as calculated in the ACS, in standard deviations.

Appendix Table 3
Change in GPA with Major Switches, for STEM Starters

	(1) GPA change	(2) GPA change	(3) GPA change
Switch out of STEM	0.092*		
	(0.053)		
x distance of switch		0.062**	0.078**
		(0.029)	(0.035)
Female	0.026	0.110	0.092
	(0.052)	(0.073)	(0.084)
Black	-0.090	-0.055	0.034
	(0.077)	(0.103)	(0.107)
Hispanic	-0.210***	-0.181*	-0.088
	(0.080)	(0.104)	(0.107)
Asian	-0.113	0.009	0.062
	(0.108)	(0.138)	(0.160)
AFQT	-0.087***	-0.069	-0.056
	(0.033)	(0.044)	(0.045)
SAT math change			0.032
			(0.062)
Male pct change			-0.042
			(0.050)
Black pct change			-0.058
			(0.061)
Hispanic pct change			0.004
			(0.055)
Asian pct change			-0.013
			(0.072)
Constant	0.133***	0.116*	0.114
	(0.048)	(0.067)	(0.092)
Observations	438	225	164
R-squared	0.037	0.053	0.083

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The sample in column 1 is all studnets who started in STEM. The sample in columns 2 and 3 is all switchers out of STEM. The dependent variable is late GPA minus early GPA. Early GPA is GPA before the major switch, and late GPA is GPA after the switch. For students who do not switch majors, early GPA is the first two years of college and late GPA is the last two years of college. Major distance is measured as described in Section 3. AFQT is in standard deviations. SAT math is the average SAT math score in the major, in standard deviations. The gender and race percentages are the makeup of the major as calculated in the ACS, in standard deviations.

Appendix Table 4

Destinations of STEM Leavers

	Share of Switchers Going to Each Major		
	All Switchers	Male Switchers	Female Switchers
Other Med/Health Services	7.8	4.1	10.8
Nursing	8.3	2.0	13.3
Agriculture	2.8	4.1	1.7
Mulitdisc/General Science	3.7	4.1	3.3
Communications	5.5	7.1	4.2
Architecture	1.8	3.1	0.8
Art History and Fine Arts	7.3	8.2	6.7
Foreign Language	0.9	1.0	0.8
Other Social Sciences	5.9	5.1	6.7
Area Studies	1.4	0.0	2.5
Psychology	10.1	10.2	10.0
Family and Consumer Science	0.5	1.0	0.0
Political Science	3.2	3.1	3.3
Economics	2.7	3.1	2.5
Public Administration and Law	2.3	1.0	3.3
Business	24.3	33.7	16.7
Philosophy and Religion	1.4	2.0	0.8
English/Literature	0.9	1.0	0.8
History	0.5	1.0	0.0
Library Science and Education	8.7	5.1	11.7

Note: The sample is all those who switch out of STEM majors. Column 1 gives the percentage of the sample going to each major. Column 2 does the same for males, and column 3 for females.