

# Differences in Persistence Patterns Between Life and Physical Science Majors: The Role of Grades, Peers, and Preparation

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## Abstract

Using longitudinal administrative data from a large elite research university, this paper separately analyzes the determinants of persistence for life and physical science majors. My results confirm much of the previous research on major persistence in the sciences, but I document that many findings are solely driven by persistence patterns in the physical sciences. For example, I show that the previously documented gender gap in science major persistence is due entirely to a large gap in the physical sciences. Despite large differences in persistence patterns between physical and life science, persistence in both fields is similarly influenced by grades. I provide suggestive evidence that students in both fields are “pulled away” by their high grades in non-science courses and “pushed out” by their low grades in their major field. In the physical sciences, analyses using within course and cohort variation show that peer quality in a student’s introductory courses has a lasting impact on the probability of persisting.

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# 1 Introduction

Lagging persistence in the sciences has been a major concern for policy makers over the past forty years. In particular, much of the research and policy on this topic has focused on improving the representation of females and minorities in science majors. While frequently lumped together into the “science” category, students in the physical and life sciences exhibit dramatically different patterns of major intent and persistence. This paper highlights the importance of disaggregating the sciences into physical and life sciences, both in conducting research and implementing policy.

One difference between this study and much of the previous literature is the selectivity of the school analyzed and the fact that it is a major research university. The findings of nationally representative studies may not reflect trends affecting top universities and these schools have a disproportionate impact. Much of the reason that policy makers are deeply concerned about science graduation rates is that it is perceived to impair global competitiveness and reduce the potential benefits of positive externalities associated with scientific research. In this regard, an elite research university is a particularly important setting to understand trends and determinants of major persistence because these students are disproportionately likely to contribute to scientific progress.

Using administrative data from a large elite research university (LERU herein), I examine the determinants of entering and then persisting in physical and life science majors. Because physical and life science persistence patterns are not yet well understood at elite universities, I devote considerable time to descriptive analysis, particularly in examining gender and ethnicity differentials. I show, for example, that failing to account for differences between physical and life sciences may lead to spurious findings regarding the importance of gender because females are over represented in the life sciences, where attrition is particularly high.

In addition to describing persistence trends, this paper investigates the impact of one’s peers on major persistence. Peer quality has been shown to be an important determinant of student performance in a variety of settings (Carrell et al., 2009; Sacerdote, 2001; Zimmerman, 2003). However, there is limited information regarding the influence of peers on major persistence and choice. Recent studies using randomly assigned roommates for identification such as Sacerdote

(2001) and Han and Li (2009) find no evidence of residential peer influence on major choice. Instead of examining residential peer effects, I investigate the existence of peer effects in one's courses. For the physical sciences, I find evidence of positive peer effects in one's core physical science classes suggesting that classmates may have a larger influence on academic decisions than roommates.

The importance of grades in determining course choice has been documented extensively (Bar et al., 2009; Fournier and Sass, 2000; Sabot and Wakeman-Linn, 1991). Given that grade inflation has disproportionately affected non-science fields, a grading gap has emerged that provides students with an incentive to defect from the sciences. Furthermore, there is evidence that females respond more strongly to grade incentives than do males, potentially exacerbating the persistence gap between men and women (Owen, 2008; Rask and Tiefenthaler, 2008).

While these phenomena affect all sciences, there exists a large amount of variation in grading standards within the sciences as well. In fact, for my data, the gap between average grades in the life and physical sciences is nearly as large as the gap between life and non-sciences. In both fields, I find that students are less likely to persist as their non-science grades improve and more likely to persist as their own field grades improve. Furthermore, I confirm that females appear more sensitive to grades; however, this differential sensitivity is limited to the physical sciences, where females are a minority group.

Since many of the factors affecting persistence are similar in the physical and life sciences, research analyzing all science majors together will in many cases arrive at qualitatively correct conclusions. However, the large body of research on the gender persistence gap need be particularly careful to distinguish between physical and life scientists.

## **2 Data**

For this study, I use longitudinal administrative data from a large elite research university. This data encompasses the entire universe of this university, including the complete transcript of courses

and grades for every entering student from 1997-2003.<sup>1</sup> These transcripts also include unique course identifiers; thus, I can exactly identify each student's peers in every course she takes. Course identifiers are constant over time facilitating the inclusion of course fixed effects. The final cohort (2003) is followed until 2008 when most (but not all) students have either graduated or withdrawn. This transcript data is matched to admissions data such as SAT scores, class rank and demographic information.<sup>2</sup>

Students entering this university are not representative of college students nationally. As shown in column 1 of Table 1, 53.7% of students in this period are white, 4.6% are black, 16.1% are Asian, 5.4% are Hispanic, 2.2% report two races and 17.2% of students fail to report a race or ethnicity. Slightly over 50% of entering students are male. The average SAT score over this period is 1358.2 and more than 75% of incoming students were in the top 10% of their graduating high school class. 33% of students enter LERU with credit for at least one college course and 24% enter with credit for calculus.<sup>3</sup> While this university is clearly not nationally representative, it is fairly well representative of students who are likely to eventually perform top level research in the sciences.

As part of the admissions process at LERU, students are asked to indicate their intended major. While students in the liberal arts sector of LERU can list either science or non-science majors, the majority of students at LERU are admitted to a specific branch and must major within that branch (e.g. students admitted into the college of engineering must intend to major in STEM). Of the 17,145 students who enter LERU during this time period, 1,634 are either missing an intended major or list "undeclared." For all analyses that require an intended major, these observations are dropped.<sup>4</sup> Of students who list an intended major, 39% intend to major in a non-STEM field, 37% intend to major in the physical sciences, and 24% intend to major in the life sciences.

Columns 2-5 of Table 1 break out descriptive statistics by intended major. Students who intend to major in the physical or life sciences are generally stronger students in terms of SAT scores,

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<sup>1</sup>One exception is transfer students who are generally not included in this data.

<sup>2</sup>Unfortunately, course instructors have not been matched to student transcripts for this university and historical faculty information is limited. A lengthy attempt to match professors to classrooms only successfully matched 30% of courses.

<sup>3</sup>In most cases, college credit is obtained by taking AP/IB courses in high school.

<sup>4</sup>Including these students and using an imputed major has little impact on results.

incoming college credits and high school rank. The physical sciences are over 70% male whereas the life sciences are over 60% female. Asian students are overrepresented in the physical sciences whereas black and Hispanic students are under represented. Based on these minimal descriptive statistics, it is already clear that the life and physical sciences attract different types of students.

### 3 Empirical Methods and Results

Graduating with a science degree is the result of first intending to major in a science field, and second, persisting in this field.<sup>5</sup> I therefore first explore patterns of intended major and then, conditional on intended major, I examine patterns of persistence.

#### 3.1 Intended Major Choice

Since different races and genders may have different preparation levels on average, I use a regression framework to better understand the type of student who intends to major in life or physical sciences. Importantly, I am not using regression in an attempt to identify causal estimates, but rather to refine the descriptive analysis. My primary question is whether the gaps between genders and races documented above can be explained by differential preparation. To address this question I use the multinomial logit function shown by equation 1 to estimate which factors contribute to declaring a life science, physical science or a non-science major.

$$P(y = j) = \frac{e^{\beta' \theta_j}}{1 + e^{\beta' \theta_j}} \quad \text{for } j = 0, 1, 2 \quad (1)$$

Table 2 shows results from the multinomial logit regression where the choices are intending to major in physical science, life science, or non-science. Consistent with the findings of Turner and Bowen (1999), many of the gender and ethnicity gaps remain when controlling for various measures of high school preparation. Controlling for observables, females are 24.2 percentage

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<sup>5</sup>While it is possible to switch to a science major after intending a non-science major, in practice less than 5% of non-science majors transfer to become science majors at LERU.

points less likely to intend to major in physical sciences and 13.4 percentage points more likely to major in life sciences. Asian students are 9.4 percentage points more likely to major in physical sciences and 2.4 percentage points less likely to major in life sciences. The magnitudes of these gaps is considerably smaller than the raw gaps, suggesting that high school preparation (or ability) accounts for some, but not all, of the intended major choices of females and Asians.

For Hispanic and black students, however, the raw gap in the likelihood of declaring a physical or life science major disappears after controlling for preparation/ability, suggesting that differences in intended majors between black/Hispanic students and white students is entirely due to differential preparation between these groups. If anything, conditional on high school performance and preparation, black and Hispanic students are more likely than white students to pursue physical or life science majors.

Consistent with the notion that stronger students tend to enter physical sciences, a one standard deviation increase in SAT score is associated with an 8.3 percentage point increase in the likelihood of intending to major in the physical sciences and a 2.8 percentage point decrease in the likelihood of intending to major in the life sciences. One's percentile in high school, on the other hand, has little effect on the propensity to major in physical science and increases the chance of intending to major in life science by 3.2 percentage points.

As expected, entering college with calculus credit strongly influences the probability of intending a physical science major, improving the likelihood by 16.6 percentage points. This effect may be because students with calculus credit have a preference for math intensive fields or because students with calculus credit have (or feel like they have) solid preparation to pursue math intensive curricula. Controlling for whether a student has taken AP/IB calculus, the raw number of incoming college credits a student has is associated with a small decrease in the likelihood of majoring in the physical sciences. This makes intuitive sense because a student with only calculus credit is pulled strongly towards math intensive fields whereas a student with calculus credit, English credit, and biology credit may have more attractive options outside of the physical sciences. The impact of incoming calculus credit and total credits is reversed for the life sciences; however, the magnitudes

of the effects are much smaller than for physical science.

Based on the determinants of entering each field, physical and life sciences are less similar than are life and non-science. In cases where data limitations or sample sizes prevent separately analyzing life, physical and non-scientists, the above regression provides some evidence that the appropriate grouping may be physical science vs life and non-science instead of non-science vs physical and life science.

## 3.2 Descriptive Analysis of Persistence

Conditional on intending to major in physical or life science, there is substantial variation in the probability of graduating with a degree in life or physical sciences across groups. Because the vast majority of students at LERU eventually earn a degree, students who fail to persist in physical or life sciences are generally switching to an alternative major. As with the initial decision to declare a physical or life science major, the persistence patterns in the life and physical sciences are very different.

### 3.2.1 Gender Gap

The most dramatic difference between life and physical science persistence patterns is that at LERU university, the gender gap in persistence is *solely* driven by a gender gap in the physical sciences. This fact is demonstrated emphatically by Figures 1 and 2.<sup>6</sup> As can be seen in Figure 1, there is essentially no difference in the persistence rates of females vs males in the life sciences. Not only do the two genders have similar graduation rates, but the trajectory with which the two groups attrit is virtually identical. Conversely, the figure for physical science shows a substantial gap between the persistence rates for males and females. Over 80% of males who intend to major in physical science successfully do so, whereas only 70% of females who intend to major in physical science persist. If one were to combine physical and life sciences in analysis, a persistence gap

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<sup>6</sup>I examine 4 year persistence rather than 6 year persistence in order to be able to include the 2002 and 2003 cohorts in all analyses. The qualitative results are identical when using 6 year persistence rates.

would appear, both because a persistence gap exists in the physical sciences and because raw persistence rates are much lower in the life sciences where females are overrepresented.

### **3.2.2 Race and Ethnicity**

The persistence gaps between black students and non-black students are qualitatively similar for life and physical sciences. Figures 3 and 4 show that black students are nearly 20 percentage points less likely to persist in both the physical and life sciences. The difference in persistence between Hispanic students and non-Hispanic students is smaller but qualitatively similar to the black/non-black gap and is shown in Figures 5 and 6. Figures 7 and 8 show persistence rates broken out by whether a student is Asian or not. Asian students are considerably more likely to persist in the physical sciences; however, their persistence pattern is similar to non-Asian students for the life sciences.

### **3.2.3 SAT Scores**

Students with higher SAT scores are more likely to persist in the sciences. This is true for both physical and life science and the relationship between SAT scores and persistence is similar across fields. Figures 9 and 10 show persistence rates separately for three SAT categories at LERU. The “high SAT” category is the top quartile of SAT scores, the “low SAT” category is the bottom quartile and the “mid SAT” category represents students with SAT scores in the interquartile range.

## **3.3 Empirical Methods: Determinants of Persistence**

While the above descriptive analysis highlights the raw persistence gaps between various groups, it fails to control for factors which may be correlated with group membership. As in equation 1, I control for observable factors which proxy for high school preparation. Furthermore, I can control for both observed and unobserved characteristics of students once they arrive. My aim in these analyses is to investigate the role of preparation, peers and grades.

Since the vast majority of major changes are from life or physical science majors to non-science fields, I focus on the probability of persisting in one’s field rather than attempting to separately investigate transitions within and out of science majors. When a linear probability model is estimated, a small fraction of students have predicted persistence rates of above 100% and thus I opt to estimate a logit model instead. Specifically, I estimate

$$P(y_{ij} = 1) = \frac{e^{\beta'X}}{1 + e^{\beta'X}} \quad (2)$$

where  $\beta'X = \beta_1GPA_{s_{ij}} + \beta_2Peers_{ij} + \beta_3X_i + \gamma_j$

$y_{ij}$  is an indicator for whether student  $i$ , taking course  $j$ , persists in her major field through the fourth year. The vector  $GPA_s$  includes each student’s overall GPA as well as separate GPAs calculated for physical science courses and life science courses. The  $Peers$  vector includes a measure of average peer quality for student  $i$  in course  $j$ .<sup>7</sup> A detailed explanation of the peer quality measure is given in Section 3.4.3. The vector  $X_i$  includes a variety of fixed student characteristics, specifically SAT score, high school percentile, race, sex, incoming college credits and an indicator for having calculus credit prior to entering college. Naturally, within individual  $i$ , cross course correlations will not be zero, thus all standard errors are clustered at the student level.

This model is estimated separately for life and physical sciences. For regressions predicting persistence in physical sciences, I include only core required physical science courses in the regression. Similarly, regressions that predict persistence in the life sciences only include core required life science courses. Focusing on large core courses facilitates the inclusion of course fixed effects and limits the analysis only to students who plausibly intend to major in their listed “intended major.”<sup>8</sup>

Including course fixed effects has two major advantages. First, students in the same course presumably have similar interests and thus the inclusion of course fixed effects controls for unobserved differences between students who choose different courses. Second, because the same

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<sup>7</sup>Student  $i$ ’s peer characteristics are calculated excluding student  $i$ .

<sup>8</sup>A small percentage of students list a science major as their intended major during admissions but take no science courses during their first year. These students are omitted from the persistence analysis.

courses are offered each year, I am able to identify the effect of peer characteristics using across time variation, holding course topic fixed. Without course fixed effects, the impact of peers would be confounded by the fact that one's peers would be determined by one's course choices (Sacerdote, 2001). Cohort fixed effects are included in some specifications in order to account for time varying unobserved factors that affect an entire cohorts persistence.

### **3.4 Results: Determinants of Persistence**

#### **3.4.1 Physical Science**

Table 3 shows the coefficients when equation 2 is estimated for physical science majors. The first column omits the course fixed effects and the last column introduces cohort fixed effects. For ease of interpretation the average marginal effect is given. When controlling for performance factors, females still are more likely to drop out of the physical sciences but the magnitude is much smaller than that implied by the raw gap shown in Figure 2. The raw persistence gap is nearly 10 percentage points and this gap drops to just 2.7 percentage points when controlling for performance and course fixed effects. The inclusion of course fixed effects may understate the persistence gap if being a female causes course choices which lead to lower persistence. However, column (1) of Table 3 shows that even when omitting the course fixed effect the gender gap in persistence is just 2.8 percentage points.

The persistence gap between black and white students is statistically and substantively insignificant once controlling for other factors. This is rather remarkable given that the raw gap in persistence is 12.4 percentage points. This phenomenon is true for Hispanic students as well, as the large raw gap is completely explained by other factors. Importantly, some of the other factors for which I control, such as GPA, may themselves be a function of one's gender or race and thus the regression might be over controlling. Regardless, the results indicate that once other factors are equalized, being black or Hispanic has no impact on persistence. Asian students are more likely to persist, controlling for other factors. When controlling for course and cohort fixed effects, Asian students are 3.7 percentage points more likely to persist than comparable white students.

High school preparation generally is a weak predictor of persistence once college grades are controlled for. This does not mean that preparation is unimportant, rather that the entire benefit to high school preparation is captured in performance in college courses. Taking calculus before entering college is associated with a 2.8 percentage point increase in persistence probabilities. However, the positive effect of calculus is only statistically significant when controlling for course and cohort fixed effects and is not robust across specifications. Given that my preferred specification is to include course and cohort fixed effects, I view this result as providing some suggestive evidence that calculus preparation may be helpful for persistence.

Performance in college courses is a critical determinant of persistence. As shown in column (3) of Table 3, a one point increase in a student's average physical science grades is associated with an 11.5 percentage point increase in the probability of persisting in the physical sciences.<sup>9</sup> Controlling for a student's grade performance in her science courses, improving overall GPA by one point decreases persistence by 3.5 percentage points. There may be small negative effects to performing well in life science courses, but this is not statistically significant. While the above results may partially reflect students simply gravitating towards their relative strengths, I show in section 4.1 that grading standard differentials across fields may lead to student attrition that is unrelated to the revelation of relative ability.

Broadly, the inclusion of cohort and course fixed effects has little impact on the coefficients in Table 3. The notable exception is that the first column of Table 3 suggests that having a larger class is beneficial to completing the major. However columns 2-3 show that this effect is completely absent when controlling for course fixed effects. The correlation between class size and major persistence is unlikely to be causal since there is no evidence of this correlation within a course.

A measure of peer quality is controlled for throughout Table 3 and I explore these results in Section 3.4.3.

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<sup>9</sup>A one point increase is the equivalent of a one letter grade increase e.g. improving from a B to an A.

### 3.4.2 Life Science

Table 4 shows the coefficients when equation 2 is estimated for life science majors. Given that no raw persistence gap exists between genders for the life sciences, it is no surprise that gender is found to have no predictive power for persistence probabilities. Unlike in the physical sciences, the raw persistence gaps for Hispanic students is not fully explained by other factors. Controlling for factors such as performance and course choice, Hispanic students are still 8.2 percentage points less likely than white students to persist in the life sciences. The raw gap in persistence between Hispanic and white students in the life sciences is 20.7 percent so nearly half of this persistence gap cannot be explained by academic performance. Although the raw persistence rate for Asian students in the life sciences is only 5.85 percentage points worse than white students, this raw gap cannot be explained by performance or preparation factors.

Just as in physical sciences, high school preparation generally is a weak predictor of persistence once college grades are controlled for. Higher SAT scores are associated with slightly lower persistence rates (1.9 percentage points per standard deviation) but calculus and other entering college credits are statistically and substantively insignificant. Given that college grades are controlled for in this regression, it is not surprising that SAT score has a slightly negative effect. One potential explanation is that students with high SAT scores but average first year college grades may lack certain study or organizational skills that make persistence difficult in life science courses which typically value these skills.<sup>10</sup>

The effect of own subject grades for life scientists is extremely similar to the effect for physical scientists. A one point increase in a student's GPA in her first year life science courses is associated with a 10.7 percentage point increase in the probability of persisting. Similarly higher grades in non-science courses are associated with lower persistence rates. A one point increase in a student's first year GPA holding science GPA constant is associated with an 8.1 percentage point decrease in persistence. The effect of non-science GPA on persistence in the life sciences is more than twice

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<sup>10</sup>Anecdotal evidence suggests that study and organizational skills may be more important in the life sciences compared to physical sciences, because the former rewards factual knowledge (which requires studying) more than the latter.

as large as for the physical sciences.

Somewhat surprisingly, receiving higher grades in one's physical science courses is associated with higher persistence in the life sciences. This effect partially reflects that students who perform well in their physical science courses are more skilled and thus more capable to persist in any field they choose. In addition, the pulling effect of high grades in the physical sciences is likely fairly small given that it is very rare to transfer into the physical sciences.<sup>11</sup>

As with the physical sciences, there is a correlation between class size and persistence, but this disappears when controlling for course fixed effects. Students who take larger courses tend to have lower persistence rates, but this should not be interpreted causally.

### 3.4.3 Peer Effects

In order to examine the effect of peers on an individual's persistence, I include a measure of peer persistence in the above regression. Were I to simply include the average persistence of one's classmates, I would overstate the importance of the peer effect because of the reflection problem (Manski, 1993). Since student  $i$  may impact her peer's persistence through her own persistence, the persistence of her peers is not exogenous to her own persistence. Previous research avoids conflating endogenous and exogenous peer effects by focusing on peer characteristics determined prior to college enrollment such as SAT score (Sacerdote, 2001). I follow a similar tact, but rather than examining a particular factor, I aggregate these factors to measure the propensity to persist.<sup>12</sup>

Specifically, I use the predicted values from a regression of persistence on pre-college characteristics to generate a propensity score for each student. This propensity score is a linear combination of pre-college characteristics and thus student  $i$ 's propensity score will be exogenous to student  $j$ 's persistence probabilities. Using the propensity score for each student, I calculate average propensity scores by class. Since these averages vary by semester, they are still identified with the inclusion of course and cohort fixed effects.

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<sup>11</sup>Fully 95 percent of successful physical science majors entered college intending to major in the physical sciences.

<sup>12</sup>Carrell et al. (2009) uses a similar strategy and uses pre-college characteristics to generate predicted GPA's for one's peers.

Although it seems unlikely that student  $i$  would influence student  $j$ 's propensity score, it is possible that two propensity scores are jointly determined by the admissions committee. Assuming that the admissions committee has more information regarding a student's propensity to persist than I have included in my regression, any broad goal to improve persistence in a cohort may bias estimates upwards. Because of this plausible threat to identification, my preferred estimates include cohort fixed effects to control for global admissions changes that directly affect both an individual and the pre-college characteristics of her peers. In practice, omitting the cohort fixed effects yields very similar results. When estimated without course fixed effects, the magnitude on the peer coefficient increases dramatically, but this simply reflects that students sort into classrooms and thus I do not consider it as evidence of peer effects.

Table 5 shows the results for peer effects. Row 1 shows that students are more likely to persist when their peers are more likely to persist. A 10 percentage point increase in the propensity of one's peers to persist leads to a 2.08 percentage point increase in the probability of persistence. This effect decreases very slightly when cohort fixed effects are included, suggesting that joint determination of persistence within a cohort is not a major concern. The reduced form impact of peer composition in first year courses may overstate the importance of peers in a single course. Since a student is likely to have repeated interactions with first year peers, the effect I capture is the cumulative effect of these interactions.

While the existence of peer effects is interesting in its own right, there are only clear policy implications if non-linearities exist across who benefits from high quality peers. In a world with homogenous peer effects, all redistributions or reorganizations will yield an equivalent amount of spillover benefits. To investigate the possibility of non-linear peer effects, I re-estimate equation 2 on two subsamples determined by one's own propensity score. Table 5 shows that students who are at most risk of failing to persist are also most influenced by their peers. For the bottom quartile, a 10 percentage point increase in the propensity scores of one's peers leads to a 3.53 percentage point increase in own persistence. The effect of peers on the upper quartile is much smaller and not statistically significant. This result is consistent with the findings of Carrell et al. (2009) that

low achieving students benefit most from exposure to high achieving peers.

Consistent with Han and Li (2009), I find evidence that females are more influenced by their peers than males. While both males and females benefit from exposure to higher quality peers, the effect is more than twice as large for women as compared to men. A 10 percentage point increase in the propensity scores of one's peers increases the likelihood of a female persisting by 3.70 percentage points compared to only 1.37 percentage points for males.

Unlike the physical science analysis, I find little evidence that peer effects are important in the life sciences. This may be because the substantially smaller sample size for the life sciences prevents the detection of such effects or may simply reflect a lack of peer effects in the life sciences for my sample.

## **4 Discussion and Extensions**

### **4.1 Grades**

In both life and physical sciences, improvements in own subject GPA are associated with greater persistence in that subject whereas improvements in non-science GPA are associated with transferring away from the intended major. This intuitive finding could in fact reflect optimal sorting if grades are indicative of relative strengths. In terms of maximizing each student's potential, it makes sense for a student who initially declares a physical science major to drop out if she discovers that she is not well suited to it. In particular, if students enter college with incorrect information regarding their relative strengths, grading provides a potentially effective mechanism for informing a student which major field they should choose (Stinebrickner and Stinebrickner, 2009). Unfortunately, this mechanism is only effective when grading standards are consistent across disciplines. Table 6 shows that this is emphatically not the case. As is true nationally, grading standards are dramatically different between majors at LERU.

Furthermore, the difference in average grades is not simply a reflection of differential student sorting into various majors. As shown in the third column of Table 6, students who intend to

major in physical sciences receive higher grades in their non-science courses compared to their physical science courses. One might expect that physical science majors would perform best in their physical science courses, but the opposite is true. As a result, a student who is best suited for life or physical sciences may in fact choose a non-science major if she is attracted by her higher average grades in these fields.

#### **4.1.1 Differential Gender Responses to Grades**

Rask and Tiefenthaler (2008) provides evidence that females are more sensitive to grades in determining economics major persistence and proposes that a similar phenomenon may contribute to the gender gap in the sciences. To investigate this possibility I re-estimate the above model separately for females and males. For the physical sciences, where a gender gap exists, the correlation between grades and persistence is very consistent with the hypothesis put out by Rask and Tiefenthaler.

As shown in Table 7, in the physical sciences, females are more sensitive to grades both in terms of major field performance and outside option performance. For females a one point increase in GPA in physical science courses improves the probability of persistence by 13.4 percent whereas the corresponding figure for males is only 10.7 percent. Similarly, a one point increase in overall GPA (holding constant science GPA) leads to a much steeper decline in persistence for females than for males. Interestingly, the same does not appear to be true for the life sciences. Own field grades have a similar impact on both males and females and outside options have a larger impact for males than they do for females.

While the reason for a grade response differential in the physical sciences but not the life sciences is unclear, one possibility is that student grade response is a function of perceived “minority” status as opposed to gender per se. There is insufficient evidence presented in this study to conclude anything about the causes of gender response differentials, but this study’s results as well as the findings of Rask and Tiefenthaler (2008) are consistent with the social psychology theories of stereotype vulnerability or attributional ambiguity (Crocker and Major, 1989). Essentially, these

theories hold that individuals in a minority position have a tendency to be influenced by stereotypes about one's social category. In particular, Aronson and Inzlicht (2004) find that students who exhibit signs of stereotype vulnerability are less able to gauge performance and consequently have unstable academic self-concept and efficacy. Furthermore, the authors note that "unstable efficacy is associated with increased sensitivity to performance feedback, both positive and negative" (p. 834). In other words, a female majoring in the physical sciences may have a particularly large response to grades because she is in the minority whereas females majoring in the life sciences are not a minority group.

## **4.2 Peers**

While recent influential research on peer effects finds no impact on major choices this may be due to looking at the wrong peers (Foster, 2006; Stinebrickner and Stinebrickner, 2006). Previous research obtains convincing identification through the random assignment of roommates, but it is far from clear that roommates are the peers who would be expected to impact major persistence. While my identification strategy is not as perfectly clean, my study benefits in that it examines peer effects in an important academic context. Naturally, the impact of one's roommates may have a different impact on major persistence than the impact of one's classmates, particularly one's classmates in key major courses.

Because the benefit of persistent peers is non-linear, social gains are possible by sorting students efficiently. Since students with a low propensity to persist benefit from exposure to high propensity peers and high propensity students do not seem to be brought down by low propensity peers, complete integration yields optimal results. While theoretically the implication of the non-linear peer effect is clear, in practice the impact of resorting may yield unanticipated consequences not captured in my analysis. The potential for these unanticipated consequences is highlighted by Carrell et al. (2010). Although Carrell et al. (2009) find evidence of non-linear peer effects similar to those found in this paper, Carrell et al. (2010) documents that an attempt to exploit these nonlinearities to improve the outcomes of low achievers actually negatively impacted these students.

The finding that females are more susceptible to peer influence than males is consistent with a large body of literature in social psychology (Eagly, 1978) in addition to the recent randomized peer effects study Han and Li (2009). Once again, it is theoretically possible to exploit this non-linearity to improve total social welfare, but the exact implications of actually implementing such a policy are beyond the scope of this analysis.

## 5 Conclusion

This study describes persistence in the life and physical sciences at a large elite research university. Examining the role of preparation, grades and peers, I find a large impact of grades on persistence in both fields. While preparation is strongly correlated with persistence, there is little evidence that preparation directly impacts persistence outside of its impact on college grades.

As expected, students who receive higher grades in non-science courses are more likely to transfer out of the sciences and students who receive higher own field grades are less likely to transfer out of the sciences. This mechanism is very similar for life and physical science majors, except that life science majors who perform well in physical science courses are actually more likely to persist in the life sciences. This may reflect the fact that very few students transfer between life and physical science majors and the threat to major persistence is transferring to non-science majors.

The primary descriptive finding is that males and females persist equally well in the life sciences but a large gap exists in the physical sciences. This gap narrows considerably when controlling for other factors, but even controlled estimates show that females have slightly worse persistence rates in the physical sciences. The raw persistence gap for black students compared to white students is present in both the life and the physical sciences, but can largely be explained by performance and preparation factors. Conversely, even when controlling for other factors, Hispanic students are found to have much lower persistence rates in the life sciences than white students.

This study also documents evidence of peer effects in the physical sciences but finds no evi-

dence of similar effects in the life sciences. For the physical sciences, exposure to peers who have a higher ex-ante probability of persistence is found to increase the probability of persistence. The impact of peers is shown to have important non-linearities where females and unlikely persisters experience the greatest gains from exposure to high quality peers.

## References

- Aronson, J, and M Inzlicht. 2004. The ups and downs of attributional ambiguity. *Psychological science*.
- Bar, T, V Kadiyali, and A Zussman. 2009. Grade information and grade inflation: The cornell experiment. *Journal of Economic Perspectives*.
- Carrell, SE, RL Fullerton, and JE West. 2009. Does your cohort matter? measuring peer effects in college achievement. *Journal of Labor Economics*, 27(3), 439–464.
- Carrell, SE, NBI Sacerdote, and JE West. 2010. Beware of economists bearing reduced forms? an experiment in how not to improve student outcomes.
- Crocker, J, and B Major. 1989. Social stigma and self-esteem: The self-protective properties of stigma. *Psychological review*.
- Eagly, A. 1978. Sex differences in influenceability. *Psychological Bulletin*.
- Foster, Gigi. 2006. It's not your peers, and it's not your friends: Some progress toward understanding the educational peer effect mechanism. *Journal of Public Economics*, 90(8-9), 1455–1475.
- Fournier, Gary M., and Tim R. Sass. 2000. Take my course, please: The effects of the principles experience on student curriculum choice. *Journal of Economic Education*, 31(4), 323–339.
- Han, L, and T Li. 2009. The gender difference of peer influence in higher education. *Economics of Education Review*.
- Manski, Charles. 1993. Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies*, 60(3), 531–542.
- Owen, Ann L.. 2008. Grades, Gender, and Encouragement: A Regression Discontinuity Analysis. *SSRN eLibrary*.

- Rask, Kevin, and Jill Tiefenthaler. 2008. The role of grade sensitivity in explaining the gender imbalance in undergraduate economics. *Economics of Education Review*, 27(6), 676–687.
- Sabot, R, and J Wakeman-Linn. 1991. Grade inflation and course choice. *The Journal of Economic Perspectives*.
- Sacerdote, Bruce. 2001. Peer effects with random assignment: Results for dartmouth roommates. *The Quarterly Journal of Economics*, 116(2), 681–704.
- Stinebrickner, Ralph, and Todd R. Stinebrickner. 2006. What can be learned about peer effects using college roommates? evidence from new survey data and students from disadvantaged backgrounds. *Journal of Public Economics*, 90(8-9), 1435–1454.
- Stinebrickner, Todd R., and Ralph Stinebrickner. 2009. Learning about academic ability and the college drop-out decision. NBER Working Papers 14810, National Bureau of Economic Research, Inc.
- Turner, Sarah E., and William G. Bowen. 1999. Choice of major: The changing (unchanging) gender gap. *Industrial and Labor Relations Review*, 52(2), 289–313.
- Zimmerman, D. 2003. Peer effects in academic outcomes: Evidence from a natural experiment. *Review of Economics and Statistics*.

# Figures and Tables

Figure 1: Persistence rates for Life Sciences by Gender

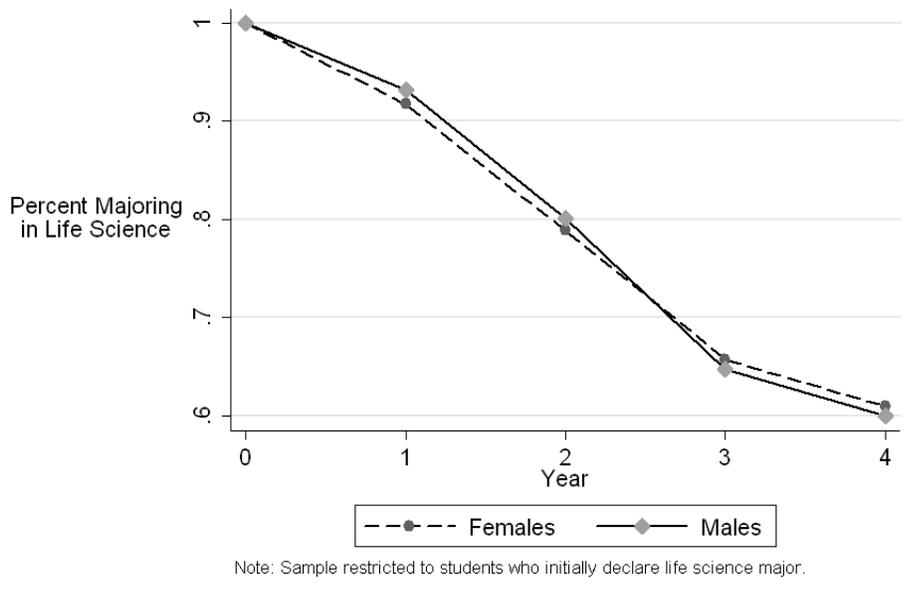


Figure 2: Persistence rates for Physical Sciences by Gender

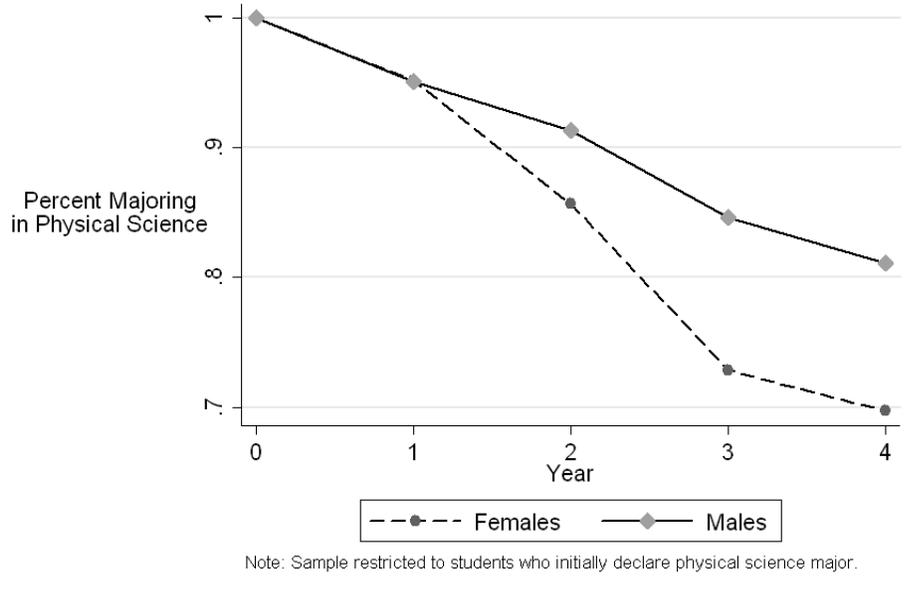


Figure 3: Persistence rates for Life Sciences by Race

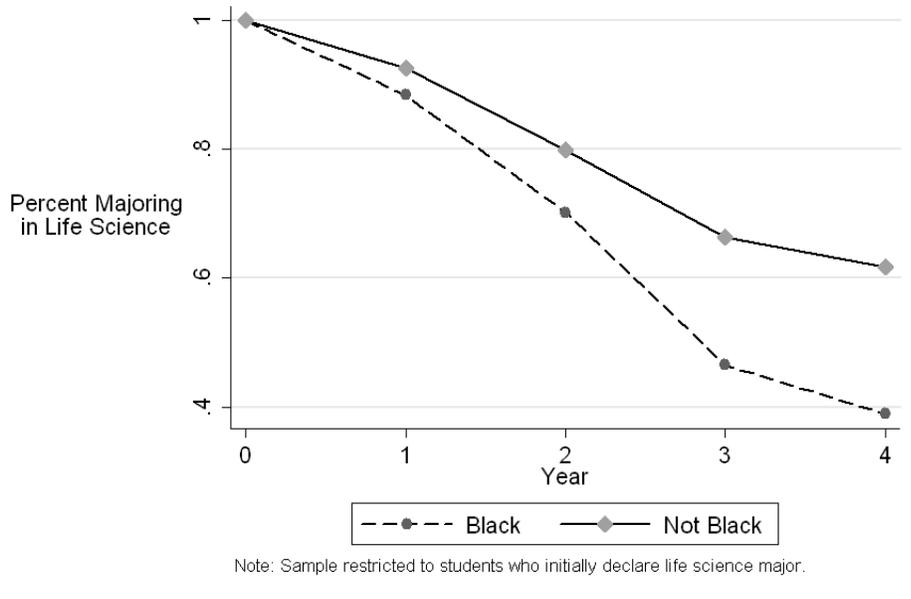


Figure 4: Persistence rates for Physical Sciences by Race

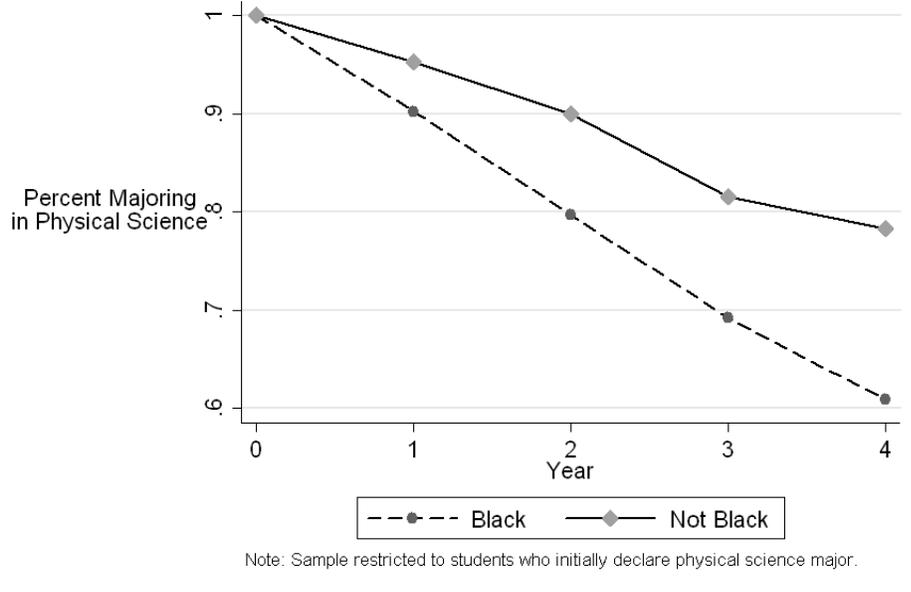


Figure 5: Persistence rates for Life Sciences by Race

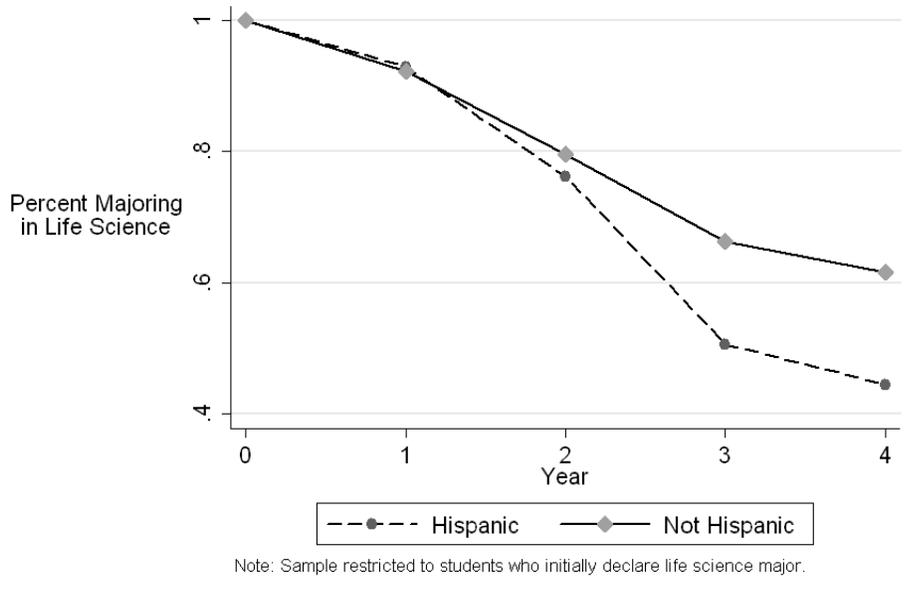


Figure 6: Persistence rates for Physical Sciences by Race

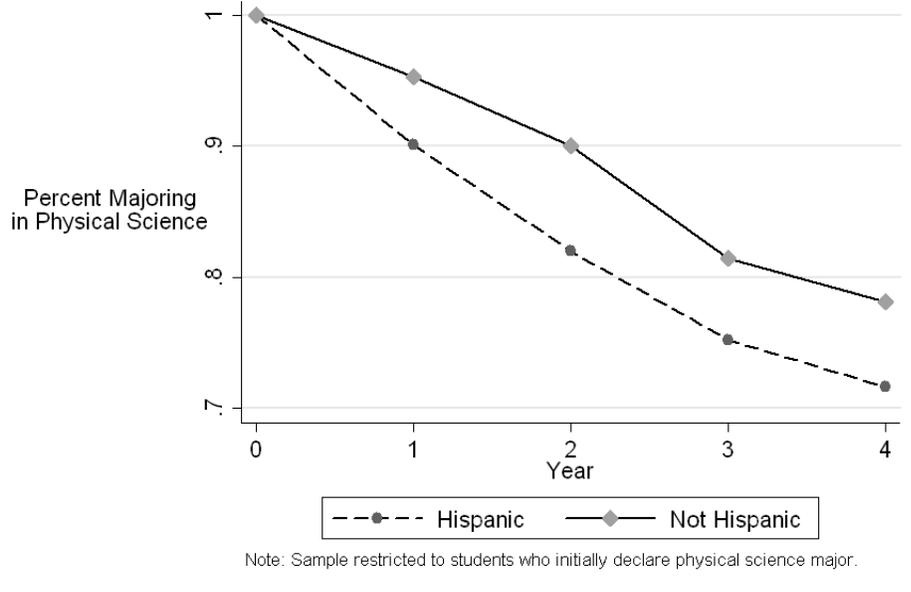


Figure 7: Persistence rates for Life Sciences by Race

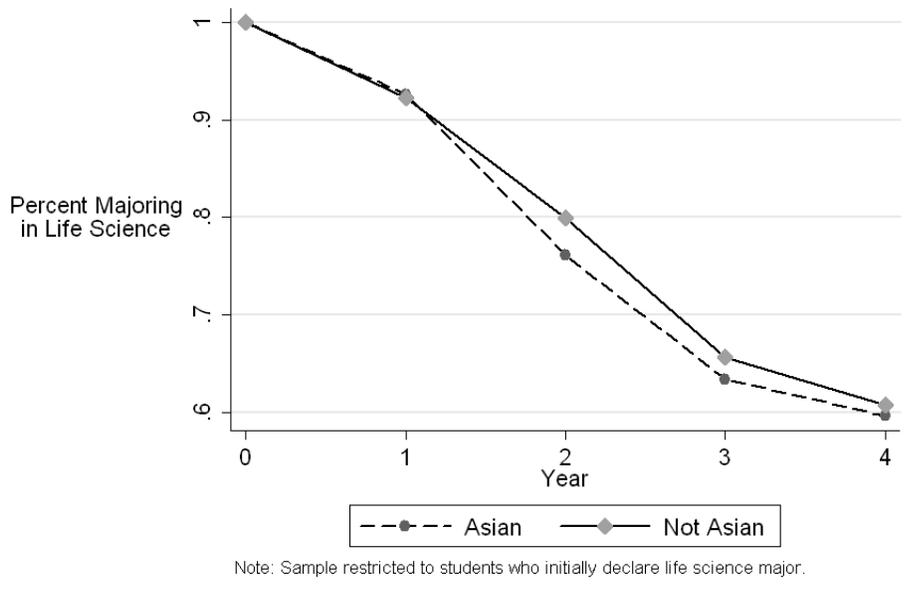


Figure 8: Persistence rates for Physical Sciences by Race

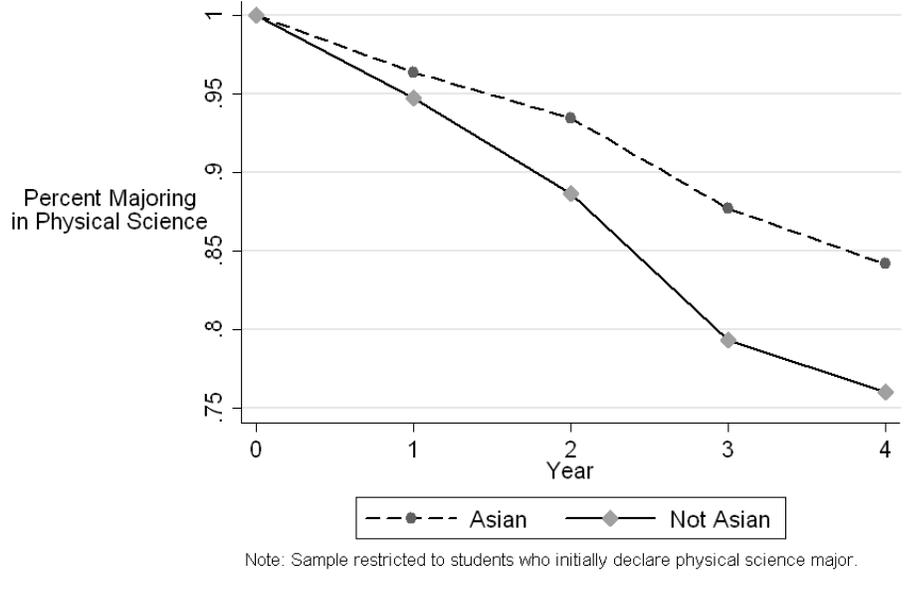


Figure 9: Persistence rates for Life Sciences by SAT

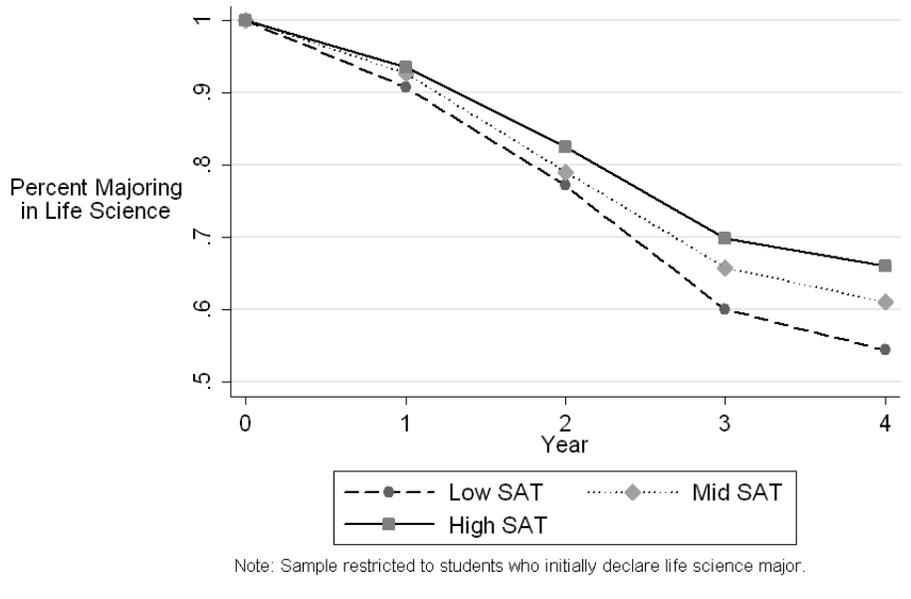


Figure 10: Persistence rates for Physical Sciences by SAT

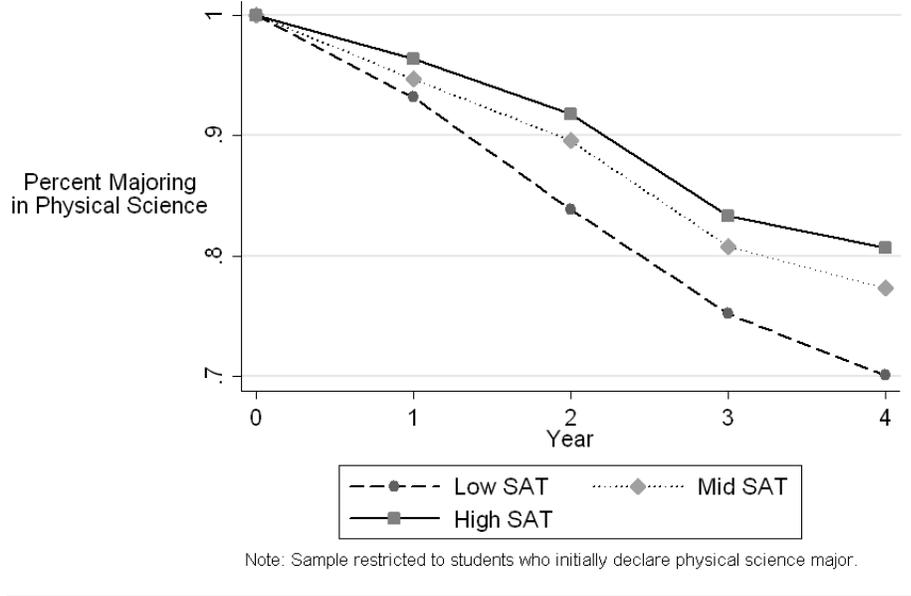


Table 1: Descriptive Statistics

	Mean	Intended Major			
		Not Science	Physical Science	Life Science	None declared
Female	0.487	0.570	0.287	0.613	0.597
Black	0.046	0.058	0.023	0.053	0.066
White	0.537	0.574	0.494	0.552	0.518
Asian	0.161	0.117	0.221	0.150	0.140
Hispanic	0.054	0.058	0.039	0.061	0.073
Multiple races reported	0.022	0.021	0.021	0.023	0.029
Native American	0.003	0.004	0.002	0.003	0.002
Race not reported	0.172	0.164	0.194	0.155	0.164
Number of incoming college courses	1.104	0.818	1.410	1.175	0.922
Incoming credit for calculus	0.237	0.153	0.341	0.229	0.196
Percentile (higher number is better rank)	0.938	0.922	0.949	0.949	0.926
SAT or equivalent	1358.242	1328.776	1398.941	1347.410	1349.001

Table 2: Intended Major

	Intended Major Field		
	Physical Science	Life Science	Non-Science
Female	-0.242*** (0.011)	0.134*** (0.007)	0.118*** (0.011)
Black	0.009 (0.024)	0.020 (0.017)	-0.060** (0.022)
Hispanic	0.026 (0.020)	0.013 (0.015)	-0.074*** (0.019)
Asian	0.094*** (0.012)	-0.024* (0.010)	-0.108*** (0.013)
Standardized SAT score	0.083*** (0.006)	-0.028*** (0.004)	-0.116*** (0.006)
Standardized class percentile rank	-0.002 (0.007)	0.032*** (0.005)	-0.094*** (0.008)
Incoming calculus credit	0.166*** (0.015)	-0.058*** (0.012)	-0.156*** (0.015)
Number of incoming college courses	-0.027*** (0.003)	0.017*** (0.002)	0.014*** (0.004)

\* Significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%. Standard errors clustered at class level reported in parentheses.

Notes: Marginal effects from a multinomial logit are given in the table. The coefficients from all three columns come from a single regression on 15,508 observations. The variables “SAT score” and “class percentile rank” have been standardized to facilitate coefficient interpretation. For the variable “class percentile rank”, lower numbers indicate a better ranking.

Table 3: Persistence in Physical Science

	(1)		(2)		(3)	
	Coefficient (std. error)	Marginal	Coefficient (std. error)	Marginal	Coefficient (std. error)	Marginal
Female	-0.284*** (0.102)	-0.028	-0.275*** (0.102)	-0.027	-0.274*** (0.102)	-0.027
Black	-0.098 (0.274)	-0.010	-0.117 (0.274)	-0.011	-0.114 (0.277)	-0.011
Asian	0.416*** (0.124)	0.038	0.414*** (0.125)	0.037	0.404*** (0.125)	0.037
Hispanic	-0.172 (0.243)	-0.017	-0.165 (0.242)	-0.016	-0.168 (0.242)	-0.017
# of incoming college courses	-0.015 (0.037)	-0.001	-0.020 (0.037)	-0.002	-0.005 (0.039)	-0.000
Incoming calculus credit	0.172 (0.169)	0.016	0.199 (0.169)	0.019	0.298* (0.180)	0.028
High school percentile	1.927 (1.192)	0.185	1.929 (1.202)	0.184	1.848 (1.221)	0.176
Standardized SAT score	-0.056 (0.066)	-0.005	-0.061 (0.067)	-0.006	-0.075 (0.068)	-0.007
GPA in 1st year life sci. courses	-0.219 (0.166)	-0.021	-0.220 (0.168)	-0.021	-0.218 (0.169)	-0.021
GPA in 1st year phys sci. courses	1.211*** (0.149)	0.117	1.201*** (0.149)	0.114	1.209*** (0.153)	0.115
GPA in 1st year courses	-0.359* (0.203)	-0.035	-0.354* (0.202)	-0.034	-0.368* (0.205)	-0.035
Class size in core phys. sci. course	0.249*** (0.035)	0.024	0.074 (0.075)	0.007	0.102 (0.073)	0.010
Course fixed effect	No		Yes		Yes	
Cohort fixed effect	No		No		Yes	
Observations	19467		19467		19467	

\* Significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%. Standard errors clustered at the student level reported in parentheses.

Notes: The dependent variable is major persistence to the fourth year in the physical sciences. The regression is restricted to students who intend to major in the physical sciences. Also included in the regression are missing indicators for cases where GPA or high school percentile is missing and peer characteristics.

Table 4: Persistence in Life Science

	(1) Coefficient (std. error)	Marginal	(2) Coefficient (std. error)	Marginal	(3) Coefficient (std. error)	Marginal
Female	0.021 -0.102	0.004	0.011 (0.102)	0.002	0.001 (0.103)	0.000
Black	-0.243 -0.218	-0.046	-0.191 (0.217)	-0.035	-0.224 (0.216)	-0.041
Asian	-0.346** -0.147	-0.065	-0.326** (0.147)	-0.061	-0.342** (0.148)	-0.063
Hispanic	-0.425** -0.204	-0.082	-0.417** (0.203)	-0.079	-0.441** (0.203)	-0.083
# of incoming college courses	-0.006 -0.036	-0.001	-0.006 (0.037)	-0.001	0.018 (0.039)	0.003
Incoming calculus credit	-0.255 -0.161	-0.048	-0.225 (0.163)	-0.041	-0.170 (0.165)	-0.031
High school percentile	-1.121 -0.983	-0.204	-1.071 (0.981)	-0.193	-0.983 (1.001)	-0.175
Standardized SAT score	-0.084 -0.058	-0.015	-0.097* (0.058)	-0.017	-0.108* (0.059)	-0.019
GPA in 1st year life sci. courses	0.621*** -0.098	0.113	0.596*** (0.098)	0.107	0.599*** (0.098)	0.107
GPA in 1st year phys. sci courses	0.324*** -0.1	0.059	0.343*** (0.100)	0.062	0.359*** (0.101)	0.064
GPA in 1st year courses	-0.442** -0.178	-0.080	-0.421** (0.177)	-0.076	-0.456** (0.179)	-0.081
Class size in core life sci. course	-0.179*** -0.041	-0.033	-0.160 (0.165)	-0.029	-0.151 (0.168)	-0.027
Course fixed effect	No		Yes		Yes	
Cohort fixed effect	No		No		Yes	
Observations	6736		6736		6736	

\* Significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%. Standard errors clustered at the student level reported in parentheses.

Notes: The dependent variable is major persistence to the fourth year in the life sciences. The regression is restricted to students who intend to major in the life sciences. Also included in the regression are missing indicators for cases where GPA or high school percentile is missing and peer characteristics.

Table 5: Impact of Average Peer Propensity Score

Panel A: Physical Sciences				
	Course FE	Marginal	Course & Cohort FE	Marginal
All students	2.181*** (0.582)	0.208	2.160*** (0.560)	0.205
Bottom 25th percentile of propensity scores	2.889*** (0.986)	0.360	2.834*** (0.954)	0.353
Top 25th percentile of propensity scores	0.469 (1.367)	0.038	0.599 (1.291)	0.048
Females	2.968*** (0.975)	0.347	3.176*** (0.927)	0.370
Males	1.709** (0.752)	0.146	1.600** (0.741)	0.137
Panel B: Life Sciences				
	Course FE	Marginal	Course & Cohort FE	Marginal
All students	-0.279 (0.767)	-0.050	0.396 (0.782)	0.071
Bottom 25th percentile of propensity scores	1.582 (1.939)	0.268	1.642 (1.974)	0.271
Top 25th percentile of propensity scores	0.264 (1.514)	0.043	2.273 (1.593)	0.361
Females	-0.201 (0.901)	-0.035	0.433 (0.933)	0.075
Males	-0.621 (1.525)	-0.114	0.272 (1.559)	0.050

Table 6: Grading Standards by Course Type and Student Intended Major

	All Students	Intended Major		
		Not Science	Physical Science	Life Science
Non-Science Course	3.33	3.31	3.35	3.39
Physical Science Course	3.13	3.08	3.16	3.06
Life Science Course	3.21	3.07	3.17	3.27

Table 7: Impact of Grades on Persistence for Males and Females

Panel A: Physical Sciences

	Females	Marginal	Males	Marginal
GPA in 1st year life sci. courses	0.034 (0.253)	0.004	-0.416* (0.239)	-0.036
GPA in 1st year phys. sci. courses	1.150*** (0.250)	0.134	1.256*** (0.197)	0.107
GPA in 1st year courses	-0.608* (0.352)	-0.071	-0.293 (0.257)	-0.025

Panel B: Life Sciences

	Females	Marginal	Males	Marginal
GPA in 1st year life sci. courses	0.617*** (0.124)	0.107	0.542*** (0.167)	0.099
GPA in 1st year phys. sci. courses	0.292** (0.126)	0.050	0.521*** (0.167)	0.095
GPA in 1st year courses	-0.399* (0.225)	-0.069	-0.547* (0.286)	-0.100