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Attribution Bias in Major Decisions: Evidence from the United States Military Academy

Abstract

Using administrative data, we study the role of attribution bias in a high-stakes, consequential decision: the choice of a college major. Specifically, we examine the influence of fatigue experienced during exposure to a general education course on whether students choose the major corresponding to that course. To do so, we exploit the conditional random assignment of student course schedules at the United States Military Academy. We find that students who are assigned to an early morning (7:30 AM) section of a general education course are roughly 10% less likely to major in that subject, relative to students assigned to a later time slot for the course. We find similar effects for fatigue generated by having one or more back-to-back courses immediately prior to a general education course that starts later in the day. Finally, we demonstrate that the pattern of results is consistent with attribution bias and difficult to reconcile with competing explanations.

JEL-Codes: D910, I230.

Keywords: attribution bias, college major.

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1 Introduction

When making consequential decisions, such as choosing a partner or career, people are likely to reflect on their prior experiences to inform which choice will provide them with the highest well-being. The standard economic model predicts that people will recognize the role that temporary physical and emotional states, such as inclement weather or fatigue, played in their prior experiences and will not be overly influenced by those states when making their choices.

However, theory and evidence from psychology and behavioral economics suggest that individuals may make systematic mistakes when responding to changes in physical and emotional states. In particular, a growing body of literature has found evidence of prospective mistakes in the form of projection bias (Loewenstein et al., 2003): instances in which individuals act *as if* their current temporary state will persist into the future.[1] More recently, Haggag et al. (2018) proposed a model and demonstrated evidence of retrospective mistakes in the form of attribution bias: instances in which individuals misattribute the influence of a prior temporary state to a fixed property of their utility over a good or activity. For example, Haggag et al. (2018) find that random variation in thirst experienced while sampling a new drink has a significant influence on people's later stated willingness to drink it again in the future. In this paper, we test for attribution bias in an important decision with long-run consequences: the choice of a college major. If students are subject to such attribution bias, prior incidental emotional and physical states during initial exposure to academic subjects may have undue influence on their college major choice.

Specifically, we test whether student fatigue generated by randomly assigned course schedules (i.e. "incidental fatigue") influences college major choice at the United States Military Academy (USMA). Our study design is motivated by evidence that students exhibit diminished performance in early morning courses (Carrell et al., 2011; Edwards, 2012; Dills and Hernandez-Julian, 2008) and in courses that are scheduled immediately after one or more back-to-back course (Pope, 2016; Shapiro and Williams, 2015), presumably due to heightened levels of fatigue. We hypothesize that the level of incidental fatigue students experience in a course may extend beyond their coincident performance; influencing their judgment of the overall corresponding subject and thus their resultant college major choice.

Our study employs two unique approaches to identify the effects of incidental fatigue on major choice. For both of these approaches we take advantage of the fact that students schedules are randomly assigned conditional on their registered courses and whether they are a Division I athlete. First, we test if being randomly assigned to a first period (7:30 AM) section of a required course (e.g. Economics 101) influences

[1] e.g. (Conlin et al., 2007; Busse et al., 2015)

the choice to major in a corresponding subject (e.g. Economics). Second, we test whether random variation in the number of back-to-back courses students are assigned immediately before (on the same day of) a required course influences major choice.[2] This second approach allows us to compare students with different levels of fatigue from the exact same classroom, thus enabling us to rule out potential classroom-level effects of fatigue on major choice such as instructor fatigue or peer effects. To employ these tests, we use administrative records from USMA containing the course schedules and college major choices of 18,753 students from 2001 to 2017.

We find that students are significantly less likely to major in a course's subject area when (conditionally randomly) assigned to an early morning course. Our estimates suggest that students assigned to an early morning section of a course are approximately 10% less likely to major in a subject related to that morning course, relative to students assigned to a later time slot for the course.[3] We also find that each additional course immediately preceding a class reduces the probability that students major in a related subject by approximately 11%. Our main specifications isolate variation between students with the same set of registered courses in a semester (i.e. the same course roster), but who are conditionally randomly assigned to different timings for those courses (i.e. a different course schedule). We show that these results are robust to number of modifications and including the addition of faculty fixed effects, using a broader mapping of courses to majors. Moreover, we provide a simple falsification test against the concern that students may select (on unobservables) into preferable schedules for courses in their intended majors. We show that the same identification strategy does not predict college major when looking at the semester after students have made their college major choice (the fourth semester).

Furthermore, we find a number of patterns that are inconsistent with the neoclassical model of rational choice and better fit a model of attribution bias. Specifically, we address the hypothesis that students avoid majors sampled under fatigue because they rationally anticipate being less prepared for success in those majors. First, we find evidence that the effects of fatigue on performance are not persistent. In a subsample

[2]Courses at USMA are all 55 minutes long and only start at one of six times: 7:30 AM, 8:40 AM, 9:50 AM, 11:00 AM, 1:55 PM and 3:05 PM. A course is defined as having a back-to-back course immediately before it if there is no break between courses in the schedule prior to it. For example, if a student has one class at 8:40AM and another at 11:00AM, the 11:00 AM class will be treated as having 0 immediately preceding courses. If the student instead has an additional class at 9:50 AM, then the 11:00 AM class will be treated as having 2 immediately preceding courses and the 9:50 AM class will be treated as having 1 immediately preceding courses. Finally, the counts are reset at 1:55 PM, as all classes prior to this period will have had a lunch break in the schedule.

[3]This estimate corresponds to a 0.19 percentage point reduction relative to the mean of 1.9 percent. This baseline mean is relatively small due to the nature of the decision problem. Our approach relies on matching each of the 18 general education courses to a corresponding major (producing 14 course-to-major mappings see Table A.1 for a breakdown). Since roughly 71.31% of students enroll in majors that do not have a clear corresponding general education course (31.18% engineering, 8.06% foreign language, and 32.07% other noncorresponding majors), the dependent variable is capturing the remaining 28.69% of majors split over the 14 course-to-major mappings.

of courses that have more than one required course in the sequence (chemistry, English, math, and physics) fatigue does reduce students grades in the initial course, but has no negative effect on the subsequent required course in the sequence (in the following semesters). Second, our results across different sources of fatigue generate patterns that cannot be explained by a stable response to reduced performance. We find that while having an early morning class or a preceding class reduces the likelihood of majoring in the corresponding major by nearly the same amount of roughly 10 percent, having an early morning class or a preceding class have significantly different effects on course performance: reducing a student's GPA by 0.053 and 0.014 standard deviations, respectively. Additionally, when we conservatively control for students GPA, we find similar sized negative effects of fatigue on students likelihood of choosing the corresponding college major. Finally, we use student evaluation data to show that students give substantially lower ratings for professors and classes that are taught early in the morning, which is consistent with attribution bias.

Our results have several implications. First, we provide field evidence of attribution bias in a highly consequential decision environment. Our estimates of attribution bias are both statistically significant and large in magnitude, suggesting that increasing the stakes of a decision do not eliminate the effects of attribution bias. Second, college major choice significantly impacts earnings (Arcidiacono, 2004) and well being (Wiswall and Zafar, 2014). Understanding the factors that influence this choice can help inform students, professors, and college administrators. Finally, our results yield simple, low-cost policy prescriptions to institutions that want to increase or decrease the probability that students select a certain major. By modifying what early morning courses are offered or manipulating the breaks before certain courses, universities can nudge students toward or away from certain majors.

This paper also contributes to three distinct literatures. First, this paper expands the behavioral literature on state-dependent preferences. Recent work has found evidence of projection bias (Loewenstein et al., 2003) – behavior resulting from individuals underestimating the degree to which their current tastes will match their future tastes in other states—in a variety of settings. For example, evidence of projection bias has been documented in catalog orders (Conlin et al., 2007), automobile purchases (Busse et al., 2015), gym attendance (Acland and Levy, 2015), and—most closely related to our study—college enrollment decisions (Simonsohn, 2009). In contrast, evidence of attribution bias (Haggag et al., 2018)—behavior resulting from misattributing the influence of a temporary state to a fixed attribute of a good or activity—is much more limited. With the exception of Haggag et al. (2018), who provide evidence of misattribution of thirst in evaluating a drink and weather in evaluating a vacation destination, there is little rigorous evidence of attribution bias in economics.

Additionally, this paper builds on a literature examining the effects of fatigue on individual judgment and performance. Recent research suggests that both the time of day and prior exertion can have a significant effect on outcomes and decisions in both work and academic environments. Workers are less productive, prone to make mistakes, and more likely to be injured during night shifts (Folkard and Tucker, 2003; Smith et al., 1994) and students perform worse when they take early morning courses (Carrell et al., 2011; Edwards, 2012; Dills and Hernandez-Julian, 2008). Prior exertion also appears to have a significant influence on judgment and performance: judges become less likely to make the difficult decision to parole inmates as the number of cases they have seen in a row increases (Danziger et al., 2011), medical residents make significantly more mistakes the longer they have been on their shifts (Landrigan et al., 2004; Barger et al., 2006), and students perform worse in classes if they have attended multiple prior courses (Pope, 2016; Shapiro and Williams, 2015). While each of these studies show that fatigue affects contemporaneous judgment and performance, we are unaware of any prior studies that examine how fatigue affects future decision making.

Lastly, this paper contributes to the broad literature on college major choice. Prior research has identified a number of standard factors that influence college major choice including differential tuition and student aid (Denning and Turley, 2017; Sjoquist and Winters, 2015; Stange, 2015), expected earnings (Berger, 1988; Beffy et al., 2012; Arcidiacono et al., 2012), instructor characteristics (Bettinger and Long, 2005; Carrell et al., 2010), ability (Arcidiacono et al., 2012; Stinebrickner and Stinebrickner, 2013), and tastes and preferences (Arcidiacono, 2004; Zafar, 2013). Our paper also fits within a smaller literature on the role of behavioral influences in college major, job, and career choice, including the roles of overconfidence (Reuben et al., 2017), psychological debt aversion (Field, 2009), and social information (Coffman et al., 2017).

The remainder of the paper is structured as follows. Section II describes a conceptual framework of college major choice that accounts for attribution bias. Section III describes our study environment and data. Section IV reports our empirical strategy and primary results. Section V presents robustness tests of our results and explores the rational and psychological explanations for our findings. Section VI concludes.

2 Conceptual Framework

In this section, we discuss a simple framework for how attribution bias may affect a student's selection of a college major. The framework applies the model of attribution bias outlined by Haggag et al. (2018) to college choice. In Haggag and Pope's model of consumer choice, an agent attempts to predict her instantaneous utility of consuming c while in state s_t, having previously consumed the item in an alternative state s_{t-1}. The agent is said to demonstrate attribution bias if her predicted utility falls between her true utility in her current (or future) state and her realized utility in the prior different state, i.e. $\tilde{u}(c, s_t) = (1-\gamma)u(c, s_t) + \gamma u(c, s_{t-1})$ for some $\gamma \in [0, 1]$. In this context, s is understood as the fatigue generated by either time of day or prior courses taken in the day.

The college major choice studied in this paper departs from the stylized consumer choice model and the experiments discussed in the earlier work in a few ways. First, the "consumption" episode (i.e. each class meeting) is repeated numerous times before the retrospective decision period (i.e. the college major choice); however, the setting is almost ideal because the state is kept relatively constant across these several repeated consumption episodes.[4] Second, we narrowly define the consumption episodes as the class meeting times; however, students are likely to engage with the subject in other time periods during the semester (e.g. doing homework in the evening), a fact that works against us finding evidence of attribution bias. Third, in making a college major choice, the student is not only forecasting utility across similar consumption episodes (e.g. class meetings which may be spread across the day in future semesters), but also across episodes that may substantially differ (e.g. working in careers associated with that major).

As with prior work, we do not identify the specific mechanisms underlying the complementarity between the state and the consumption item. For example, one may experience higher utility of consuming a food when hungry due to hunger affecting the sensitivity of taste/smell receptors or through heightened attention to the taste itself (e.g. at the expense of attending to other attributes such as nutrition or texture). Likewise, in the context of this paper, incidental fatigue could lower one's utility from taking a class by diminishing goal-oriented attention broadly (e.g. see Boksem et al. (2005)) or through how any particular attribute is evaluated (e.g. by increasing irritability with an instructor's speaking style or tone that might otherwise be ignored). Beyond those attentional or mood channels, students may make misattributions over how difficult the subject is, their own subject-specific ability, or how "interesting" the subject is. Although a variety of factors such as future job characteristics, future pay, faculty, and program reputation are likely to influence a student's choice of major, a number of studies suggest that the most important factors are a student's subject-specific abilities and whether she enjoys or is interested in the subject (e.g. Beggs et al., 2008; Malgwi et al., 2005; Zafar, 2013) – thus misattributions over these factors may be particularly important. In Section 5.2, we begin the process of disentangling these channels using revealed preference and student course evaluation data. Ultimately, future work with more detailed and mixed data sources may be able to better parse the underlying channels of misattribution.

[4] More precisely, the treatment variable, class time, is held constant. The manipulated state, fatigue, may acclimate to class time as the semester progresses, but this should weaken our effects.

3 Data and Empirical Strategy

3.1 Data

Data for this study come from administrative records at the United States Military Academy (USMA) at West Point, NY and includes 233,598 student-course observations from 18,753 freshman and sophomore USMA students between the years of 2001 and 2017. USMA is a 4-year undergraduate institution with an approximate enrollment of 4,400 students. In total, USMA offers 39 majors within basic science, engineering, humanities, and social science. USMA also provides all students with the equivalent of a "full-ride" scholarship, but also requires students to attend all assigned classes, graduate within four years, and complete a 5 year service commitment in the United States Army. In spite of these unique attributes, the admissions rate, student-to-faculty ratio, class size, racial composition, and standardized test performance are similar to selective liberal arts colleges such as Williams College, Davidson College, and Washington and Lee University (Carter et al., 2017). USMA admits 10% of all applicants, has a student to faculty ratio of 7:1,[5] and limits class sizes to 18 students. The racial composition of our sample, shown in Table 1, is 72.1% white, 8.7% Hispanic, 8.5% black, and 7.2% Asian. Also, the standardized test performance in our sample reflects the selectivity of USMA, with average SAT math and verbal scores of 652/800 and 639/800 respectively.[6] While in many ways the student population is similar to other selective liberal arts colleges, there are characteristics that are unique. Only 16.5% of students in our sample are female, 16.3% have prior military service, 22.1% have prior college experience, 16.3% previously attended a military preparatory academy, 33.2% are Division I athletes, and students come from across the country with students from every state.[7]

In comparison to other colleges, students' time and schedules are highly structured at USMA. On a typical day students are required to participate in breakfast formation at 6:55 AM and breakfast from 7:05 to 7:20 AM. Depending on students schedules, some students start their first classes as soon as 7:30 AM and classes, studying, and rest occur from 7:30 AM to 4:00 PM with a break for lunch. The evening consists of intramural and varsity athletics, dinner, and an evening study period. The scheduled study period ends at 11:30 PM and students are instructed to turn their overhead lights off at 12:00 AM.[8] In addition, student schedules in the first two years consist almost entirely of required courses in basic science, humanities, and

[5] Source: https://nces.ed.gov/collegenavigator/?q=united+states+military+academy&s=all&id=197036. Accessed 9/14/2017.

[6] National averages during this time were approximately 516/800 and 501/800 for math and verbal scores, respectively. Source: https://nces.ed.gov/fastfacts/display.asp?id=171 accessed 4/17/2018.

[7] This diversity is driven by a rule that places a limit on the number of students that can come from each congressional district.

[8] Students may continue studying with a desk lamp after 12:00 AM.

social science.[9] When courses are offered is also highly structured: courses at USMA are all 55 minutes long and only start at one of six times: 7:30 AM, 8:40 AM, 9:50 AM, 11:00 AM, 1:55 PM and 3:05 PM.[10] Classes are offered on a Day 1 (A-F hours) and Day 2 (G-L hours) rotation, for a total of 12 possible course slots. Particularly important to our approach is that instead of students choosing their own schedules, USMAs registrar's office assigns the time, day, and instructor for each course. This plausibly random assignment to course scheduling is a key component of our identification strategy. Also important to our analysis is the structured process of selecting a major. Within the years of our sample, students declare a major during the first semester of their sophomore year.[11] Students then begin coursework in their selected major the first semester of their junior year.

The structured nature of the first two years for students at USMA has several characteristics that make this setting ideal for testing the relationship between course scheduling and major choice. Because all students are either required to take or test out of a set list of courses, students have nearly identical schedules. This allows us to compare outcomes among students who take the exact same roster of courses in a semester. Also, because students all select their majors at the same time during their third semester, we are able cleanly identify which courses could plausibly influence a student's major choice. Additionally, because students do not have control of when they take classes during the day, it is plausible that students are conditionally randomly assigned to class hours.[12] Finally, because students face strict consequences for missing courses, we do not have to be concerned with differential attendance driving our results.[13]

The key assumption in our identification strategy is that students are conditionally randomly assigned to instructors and course schedules. The unique environment at USMA, where students have little control over which courses they take and do not choose their instructors or course hours, makes self-selection into courses at certain times with certain instructors unlikely. However, we formally test randomization to course schedules in Tables 2 and 3. In Table 2 we compare observable characteristics between students assigned to first period courses and courses at other periods during the day, where each observation is at the student-

[9] See Appendix Figure 1 for a list of required liberal arts courses and corresponding majors.

[10] These listed start times are for years 2007-2017. From 2001 to 2006, classes at USMA started at 7:35 AM, 8:40 AM, 9:45 AM, 10:50 AM, 1:50 PM, and 2:55 PM. Given the similarity of these start times to those from 2007-2017, we treat these courses as if they started at 7:30 AM, 8:40 AM, 9:50 AM, 11:00 AM, 1:55 PM and 3:05 PM, respectively.

[11] USMA tradition is to refer to freshman, sophomores, juniors, and seniors as Plebes, Yearlings, Cows, and Firsties, respectively. We use the more common terminology for clarity. Beginning with the graduating class of 2019, students declared a major in between their first and second year, but could easily change majors prior to their junior year. We include these students in our sample, but our results are robust to excluding the class of 2019 and 2020 and only including observations from the first year.

[12] While there are certain factors that influence when a student takes a class (e.g. certain courses are not offered at all hours and student athletes practices that conflict with certain periods), they are observable to the researcher and assignment to classes at a certain hour are plausibly randomly assigned conditional on these factors.

[13] Students who have an unexcused absence are typically required to spend several hours during the weekend walking along a line in a formal uniform.

course level. In column 1 of Table 2 we simply regress the individual characteristics onto assignment to a first period course, controlling for year fixed effects. With 3/11 characteristics differing at the 1% level and a joint F-test p-value of 0.00, the observable characteristics are not unconditionally balanced across first and other period courses. This, however, is unsurprising. Because not all courses are offered in every period, assignment to a first hour course is partially a function of a student's course roster. Students with different course rosters are also likely to be different on other dimensions, so controlling for students course composition is an important precursor for conditionally random assignment to courses. Additionally, Division I athletes have practice schedules that often keep them from taking afternoon courses, which also changes the likelihood that they are assigned to early morning courses. Therefore, in column 2 of Table 2 we control for both course roster fixed effects and an indicator for Division I athlete status. The student characteristics appear to be balanced once these controls are added, with no characteristics varying between first and other hour courses at the 5% level, a joint F-test p-value of 0.15, and only age of students varying at the 10% level. Adding course fixed effects in column 3 does little to change the coefficient or joint test values. Column 4 adds a more flexible control for athlete schedules, including a sport-by-semester fixed effect instead of a general indicator. This control does make age differ across course times at the 5% level, but improves the overall balance: increasing the f-stat p-value from 0.18 to 0.57. Furthermore, an age difference of -0.001 years is likely to be economically insignificant. Adding faculty fixed effects in column 5 makes little difference for the individual or joint balance across characteristics. Altogether, columns 2-5 of Table 2 suggest that assignment to first hour courses is random after controlling for course composition and Division I athlete status.

In Table 3, we also examine whether the variation in the number of preceding courses a student has before a course appears to be conditionally random. In column 1 we do not control for student course roster fixed effects and find some differences in characteristics among students with different numbers of preceding courses. Specifically, 1/12 variables differ at the 1% level in column 1 and the Joint F-statistic p-value is 0.02. However, including course roster fixed effects and controls for Division I athlete status eliminates the imbalance across characteristics. In columns 2-4—which add course roster fixed effects, course fixed effects, and sport-by-semester fixed effects, respectively—no variables significantly differ and all generate F-statistic P-values greater than 0.95. Adding unique course fixed effects in column 5 does lead the sex of students to vary at the 5% level. However, no other variables differ at any significance level and the joint F-statistic has a p-value of 0.39. Similar to our findings in Table 2, Table 3 suggests that variation in the number of preceding courses is conditionally random after controlling for course roster fixed effects.

4 Methods and Results

4.1 Methods

We start by examining the relationship between assignment to a 7:30 AM course and whether a student selects a corresponding major. This approach is similar to that taken by Carrell et al. (2011) to study the effects of school start time on performance at the United States Air Force Academy (USAFA).[14] To identify the causal effects of being assigned an early morning class on college major choice, we estimate the following equation:

$$Y_{icjts} = \beta F_{icts} + \delta_1 X_i + \delta_2 \frac{\sum_{k \neq i} X_{kcts}}{n_{cts} - 1} + \delta_3 R_{it} + \gamma_c + \phi_j + \lambda_t + \epsilon_{cjts} \tag{1}$$

where Y_{icjts} is an indicator for whether individual i in course c with professor j during time-slot s in year t chooses to major in a corresponding subject area. F_{icts} is an indicator of whether the course is an early morning course (7:30 AM). X_i is a vector of student characteristics including: age, sex, race/ethnicity, SAT math and SAT verbal test scores, and leadership scores. $\frac{\sum_{k \neq i} X_{kcts}}{n_{cts}-1}$ is a vector of the average characteristics of a student's peers within a course. Particularly important to our analysis is our course roster fixed effect (R_{it}), which is a fixed effect for the particular combination of courses a student takes in a given semester.[15] By comparing outcomes only among students who share the exact same combination of courses, we are able to isolate the effect of scheduling differences on course outcomes. Additionally, γ_c is a course fixed effect (e.g. Calculus I or World History),[16] ϕ_j is an instructor fixed effect, and λ_t is a year fixed effect. Our estimates also include fixed effects for the number of courses a student has assigned on that same day and for the number of courses immediately preceding each course. These variables are intended to isolate the fatigue generated by early morning assignment from other sources of fatigue such as exertion.[17] In the

[14] A more exact extension of their approach would be to estimate the effects of being assigned an early morning course on whether students select the corresponding major(s) of any of their classes throughout that day (rather than just for the first course of the day). However Carrell et al. (2011) only find performance effects throughout the day when the first course started at 7:00 AM. When courses started at USAFA at 7:30 AM (as at USMA) Carrell et al. find students perform poorly in the 7:30 AM course but there are no residual effects of an early morning courses on the performance of students later in the day. We reproduce this finding in our context: assignment to a 7:30 AM course reduces performance in the course, but does not affect performance in subsequent courses. For this reason we focus our analysis only on the first hour courses.

[15] All students are required to complete or test out of all assigned first and second year courses. Additionally, several courses have honors sections that students are admitted into by either (a) having high academic qualifications or (b) expressing strong interest in majoring in the subject area. To avoid selection into testing out of certain courses or taking honors sections biasing our results, we include a fixed effect for each combination of courses students take. One caveat is that we treat all language courses as being the same course, as language courses are the courses over which students can exert the greatest amount of choice, and including all combinations of languages and core courses would begin to closely approximate an individual fixed effect.

[16] Honors and non-honors sections are treated as different courses.

[17] By controlling for the number of courses and immediately preceding courses, our equation estimates the difference in major choice from those with similar workloads (e.g. both have a break before class and have the same number of courses they have prepared for), but one is assigned 7:30 AM section and another is assigned a later section. Our estimates are robust to excluding these controls, as can be seen in appendix Table A.2.

above equation, our parameter of interest is β which measures the effect of being assigned an early morning course on the probability of a student selecting a major in that early morning course's subject area. We estimate this equation with ordinary least squares, clustering our standard errors by both individual and course section.

In our second empirical strategy, we estimate whether the number courses of immediately preceding a required course affects major choice. This design draws motivation from studies such as Pope (2016) and Shapiro and Williams (2015), which find that students perform worse as they spend more time in school on a given day. Additionally, this approach relates to a broader literature that links sustained effort to a drop in performance across a number of domains (e.g. Folkard and Tucker, 2003; Landrigan et al., 2004; Danziger et al., 2011). To identify the effects of the number of preceding courses on college major choice, we estimate:

$$Y_{icjts} = \beta_1 Preceding_{icts} + \delta_1 X_i + \delta_2 \frac{\sum_{k \neq i} X_{kcts}}{n_{cts} - 1} + \delta_3 R_{it} + \gamma_{ctjs} + \lambda_t + \mu_i + \epsilon_{cjts} \tag{2}$$

where $Preceding_{icts}$ is a count of immediately preceding courses and γ_{ctjs} is an instructor-semester-section-course (i.e. unique class) fixed effect. All other variables are identical to those specified in Equation 1. More specifically our regressor of interest, $Preceding_{icts}$, is defined as the streak of courses (i.e. with no break in between) before the course of interest. For example, if a student has one class at 8:40AM and another at 11:00AM, the 11:00 AM class will be treated as having 0 immediately preceding courses. If the student instead has an additional class at 9:50 AM, then the 11:00 AM class will be treated as having 2 immediately preceding courses and the 9:50 AM class will be treated as having 1 immediately preceding courses. Finally, the counts are reset at 1:55 PM, as all classes prior to this period will have had a lunch break in the schedule. The variation in the preceding course measure is shown in Appendix Table A.11.

In addition to providing another source of variation in fatigue, this second approach allows us to exploit variation in fatigue within specific classrooms. Using this within-course variation in our estimates is attractive because it allows us to rule out potential classroom level effects of fatigue on major choice, such as the fatigue of the instructor or peer effects.

4.2 Results

We present our estimates of equations (1) and (2) in Panel A and B of Table 4 respectively. Columns 1-3 of Panel A report the estimates of the effects of early morning classes outlined in equation (1).[18] In each

[18]Estimates that replace the dependent variable with a broader mapping of courses to majors and estimates that exclude athletes can be found in Appendix Tables A.5 and A.6. Our results are robust to these alternate specifications. Mappings of

specification in Panel A our estimate of β is negative and statistically significant, indicating that assignment to a 7:30 AM course decreases the probability that a student will select a corresponding major. Column 1 of Table 3, which does not control for faculty, demographic, or peer demographic controls, suggests that assignment to an early morning course decreases the probability that a student majors in a corresponding major by 9.99%, or 0.19 percentage points (significant at the 5% level). Controlling for instructor fixed effects, demographic controls, and classmate demographics in columns 2 and 3 has no effect on our estimates: each of these specifications indicate that assignment to an early morning course reduces the probability that a student chooses a corresponding major by 10.18% and 10.15 % respectively, or 0.19 percentage points (all significant at the 5% level).[19]

In Panel B of Table 4 we estimate whether prior exertion also influences what major a student selects. Specifically, examine whether the number immediately preceding courses a student is assigned—a different source of incidental fatigue—affects whether students choose a corresponding major. Our results corroborate our findings in Panel A and further suggest that fatigue reduces the probability that students select a corresponding major. In column 1 of Panel B we estimate Equation 2 with course subject fixed effects instead of unique course fixed effects.[20] In this estimate we find that each immediately preceding course decreases the probability that a student selects a corresponding major by 7.94 % or 0.15 percentage points (significant at the 5% level). In each column 2-3 of Panel B we control for unique course fixed effects, additionally including demographic controls in column 3. These specifications control for any classroom-specific variation such as the level of preparation and fatigue of the instructor, the light, smell, and temperature in the room, and the behavior of the students within the class. Both of these specifications provide consistent evidence that increasing the number of back-to-back courses before a class reduces the probability of majoring in a related subject. In column 2 we find that each immediately preceding course decreases the probability that a student chooses a narrowly defined corresponding major by 11.71%, i.e. 0.22 percentage points (significant at the 1% level). Adding demographic controls in column 3 does not change our estimates or precision.

4.3 Effect Magnitudes

To provide context for our results, in Table 5 we estimate four benchmark comparisons for our results. The first two estimates exploit similarly (conditionally) randomly assigned influences (instructor characteristics),

courses to broad and narrow majors can be found in Appendix Table A.1.

[19]While we use a series of controls and fixed effects in our main specifications to ensure conditional randomization, we see similar results in simplified versions of our primary models. Tables A.2 and A.3 show estimates of simplified versions of our models alongside estimates of our primary models.

[20]This specification is nearly identical to the specifications outlined in Equation 1 and estimated in Table 3, except with a treatment of number of preceding courses in place of a treatment of 7:30 AM course.

while the latter two use potentially endogenous regressors. The first benchmark is motivated by Carrell et al. (2010), who find that female students are more likely to select STEM majors if the instructors in their general education STEM courses are female as well. In column 1 of Table 5, we examine the effect of having a female instructor in a general education STEM course on the likelihood that a female student enrolls in the corresponding major. We find that women are about 0.76 percentage points more likely to choose a corresponding major when their instructor is female, a point estimate that is about four times larger in absolute magnitude than our estimated effects of early morning course assignment and each immediately preceding course.[21]

The second benchmark is the effect of being randomly assigned to an instructor with better prior course evaluations for that same course. In column 2 of Table 5, we find that assignment to an instructor with a 1 standard deviation higher prior aggregate course-evaluation average increases the probability that a student majors in a corresponding course by 0.19 percentage points.[22] This estimate is nearly identical in absolute magnitude to our effects of early morning courses and immediately preceding courses on major choice.

In column 3 of Table 5 we estimate the correlation between a student's course evaluation and major choice. While this relationship is not causal, we find that a student who gives a course a 1 standard deviation higher rating is 0.70 percentage points more likely to choose a corresponding major. This suggests that our effects of fatigue are comparable with approximately a 0.27 standard deviation drop in instructor evaluations. In column 4 we similarly examine the correlation between student performance and major choice and find that a 1 standard deviation improvement in grades corresponds to a 1.34 percentage point increase in the probability that a students select a corresponding major. Therefore, our estimates are comparable with approximately a 0.14 standard deviation drop in performance.

While the magnitude of the effects of fatigue on major are large in percent terms (with both 7:30 courses and each preceding course decreasing the probability that students major in a related subject by approximately 10%), our estimates are small in percentage point terms due to the low probability that students eventually choose majors that correspond to required courses at USMA. A reasonable question is whether our estimates would grow in percentage-points if the baseline probability of choosing a major increased. In Appendix Table A.10, we estimate our results separately by low- and high-popularity majors.[23] Although

[21]We find that assignment of female students to either male or female instructors in STEM courses is uncorrelated with student characteristics, which allows us to estimate a causal relationship between instructor assignment and major choice.

[22]We construct our measure of prior course evaluations by averaging all of an instructors prior evaluations within a course and then creating a z-score measure within a course. Similar to our findings in column 1, we find that student observable characteristics are uncorrelated with prior course characteristics.

[23]Low-popularity majors include Chemistry, English, Math, Philosophy, Physics, US History, and Western Civilization. High-popularity majors include American Politics, Economics, Geography, International History, IT/Computer Science, and Psychology.

these estimates lack the precision of our primary specifications, we find that the percentage point effect size scales reasonably with the baseline popularity. In panel A of Appendix Table A.10, we find that assignment to a 7:30 AM section of a course reduces the probability that students choose a corresponding major by 0.11 percentage points (or 12.86%) in low-popularity majors and by 0.36 percentage points in high-popularity majors (or 8.64%), with neither estimate being statistically significant. In panel B of Appendix Table A.10 we find that that each preceding course reduces the probability that students choose a corresponding major by a statistically insignificant 0.03 percentage points (or 4.11%) in low-popularity majors and by 0.49 percentage points (or 11.76%) in high-popularity majors, which is significant at the 5% level.

5 Mechanisms

5.1 Fatigue and Attribution Bias

Our analysis is motivated by the assumptions that early or back-to-back courses increase student fatigue, and that the resultant fatigue in a class reduces a student's overall enjoyment of it (i.e. that the class experience is state-dependent with respect to fatigue). An ideal dataset would allow us to measure the effect of the course schedule assignment on fatigue (i.e. a manipulation check) and that a student's experience in a course is worse when fatigued (i.e. a first stage test of state-dependence). In the absence of these measures, we provide some suggestive evidence using the available large-scale administrative data. First, as a partial attempt at a manipulation check, we test whether students grades in a class are affected in the expected direction by course schedules. Second, to shed light on state-dependence, we combine the class schedule data with course evaluations (over the subset of years for which there is coverage: 2008 to 2017). While there is no overall assessment of the class, and many of the questions ask students to evaluate the instructor, the pattern may shed light on students enjoyment of the course. For both sets of analyses, we repeat our primary specifications but change the outcome variables to student performance or course evaluation rather than college major choice.

In column 1 of Panel A of Table 6 we find that assignment to an early morning course reduces performance by 0.049 standard deviations (significant at the 1% level).[24] Including instructor fixed effects, student demographics, and peer demographics in columns 2 and 3 slightly increases the magnitude of these estimates to 0.053 standard deviations. Panel B of Table 6 similarly shows that each additional immediately preceding course reduces performance by between 0.014 and 0.017 standard deviations. Altogether our results in Table

[24] Normalized grades are calculated by taking the distance in standard deviations from the course code-by-semester mean grade. This is the same approach taken by Carrell et al. (2011).

6 are consistent with early morning courses and preceding courses increasing student fatigue and reducing student performance.

The data underlying the student evaluation exercise come from anonymous, voluntary, end-of-the-semester, online evaluations by USMA students starting in 2008. Despite these evaluations being optional, we maintain a 62% response rate among the courses in our sample. Each course evaluation includes 10 questions that were determined at the institutional level.[25] Students who start an evaluation are required to answer all questions to submit the evaluation, so we have even coverage of all 10 questions. We verify that evaluation response rates are not significantly predicted by assignment to a 7:30 AM course nor by the number of immediately preceding courses. Table 7 reports the analysis of the student evaluations. Columns 1-3 report the effect of having an early morning course on evaluations for different specifications and columns 4-6 report the effect of having immediately preceding courses. The first row shows the effect on an aggregate evaluation that puts equal weight on each of the 10 standardized questions regarding the instructor (5), course (2), schedule (2), and peers (1). Regardless of the specification, having an early morning course decreases a student's aggregate evaluation of the course by between 0.14 0.15 standard deviations. Although the effect size varies some for each specific question, the effect of an early morning course is highly statistically significant for each student evaluation question and ranges from 0.07 to 0.15 standard deviations. By contrast, we do not find significant effects of the number of immediately preceding courses.

Several issues complicate the interpretation of the student evaluation data. First, it could be the case that students treat course evaluations as a recommendation to future students, and thus attempt to adjust for the influence of fatigue on their enjoyment before answering. Under that interpretation, the analysis of course evaluations would itself be a test of attribution bias rather than the first-stage verification of state-dependence. Second, we do not have an overall assessment of the course or course content, but rather a set of questions heavily representing instructor performance. It is perhaps then unsurprising that we find negative effects for the 7:30AM empirical strategy which may reflect instructor fatigue, but do not find it in immediately preceding courses results, where instructor and peer fatigue are held constant. Ultimately, while columns 1-3 are suggestive of some scope for state-dependence, the evaluation data are limited in what they can say.

[25]Departments and course directors can (and do) add additional questions. However we focus our analysis on the 10 questions asked to all students in our sample.

5.2 Rational Response

While our results in Table 6 strongly suggest that students in early morning courses and with immediately preceding courses are fatigued, they also open the possibility that the decrease in the probability that students select a corresponding major is not driven by attribution bias, but a rational response to reduced performance. Specifically, students who were fatigued in certain courses because of random variation in their course schedules may be aware that they would have performed better in a later course or after a break *and* are aware of the influence of course schedule variation on other aspects of the college major choice, such as enjoyment of the subject materials. In spite of this understanding, students may still decide not to pursue a corresponding major because their schedule caused them to believe that they are less prepared to succeed in that subject.

One reason to doubt that this rational channel could fully explain our primary results is the difference in magnitude of the estimates between Panel A and B in Table 6. In Tables 4, our estimates of the effects of early morning courses and preceding courses on major selection are nearly identical. If both of these effects were driven entirely through differential preparation, we would also expect the effects of early morning courses and preceding courses on performance to be similar. However, our estimates of the effects of early morning courses on performance in columns 1-3 of Panel A in Table 6 are approximately four times the magnitude of the effects of preceding courses on performance reported in columns 1-3 of Panel B.

Another reason to question whether a rational response to reduced preparation could be driving our results is the implied magnitude of the effect of reduced preparation on college major choice. Our estimates of equation (1) in Tables 4 and 6 suggest that first hour courses reduce the probability that students select a corresponding major by 9.45% and course performance by 0.053 standard deviations. If the negative effect on major selection is completely driven by a rational response to lesser preparation, then linearly extrapolating our estimates suggests that an average 0.56 standard deviation reduction in preparation, or roughly the difference between a B and B-, could be enough to eliminate all majors in core subjects.[26] Our estimates of equation (2) in Tables 4 and 6, which indicate that each preceding course reduces the probability that a student majors in a related course by 10.5% and reduces performance by 0.014 standard deviations, suggest an even more improbable effect of preparation on major choice. Linearly extrapolating these estimates suggests that if our results are driven by a lack of preparation, then an average reduction of preparation of

[26] We calculate this value by first identifying that in our preferred specification, first period assignment reduces the probability that a student majors in a subject by 9.45%. To determine the drop in grade that would eliminate all majors, we divide the effect of first hour course on grade (0.053 standard deviations) by 9.45% or 0.0945. The standard deviation of performance in our sample is 0.73 grade points, so a 0.56 standard deviation reduction in performance is equivalent to a 0.41 grade point drop. The difference between a B and a B- is 0.33 grade points.

only 0.13 standard deviations could be enough to eliminate all majors from core courses. With the caveat that these estimates are extrapolated far beyond our existing estimates, we find it unlikely that a decline in preparation in the range of 0.13-0.56 standard deviation could lead all students in core courses to select different majors at USMA.

To further investigate whether it is plausible that students avoid majors due to persistent disadvantages caused by assignment to a 7:30 AM course or multiple courses in a row, we test whether students assigned to those conditions perform worse in the next required class in the same subject area in Tables 8 and 9.[27] Our findings in Table 8 are somewhat surprising: our estimates in columns 1-4 of Panel A indicate that assignment to a 7:30 section has a positive, and marginally statistically significant, effect on performance in the next required subject area course of between 0.016 and 0.025 standard deviations. One potential concern is that students in courses identified in Panel A of Table 8 do not experience the same effects of 7:30 AM courses as identified in Table 6. Specifically, if there were little to no immediate effect of 7:30 AM courses on performance in the courses identified in Table 8, then we would be uncomfortable generalizing these results to the classes that are not followed by a required course. However, our results in columns 1-4 of Panel B of Table 8 indicate that the immediate effects of assignment to a 7:30 AM course on performance in these initial subject area courses (-0.057 to -0.064 standard deviations) is similar to the overall effects of 7:30 AM course assignment on performance reported in Table 6 (-0.049 to -0.053 standard deviations). Together the patterns in Panel A and B of Table 8 suggest that persistent negative effects of early morning course assignments on performance are unlikely to be large and that students may actually slightly benefit in the long-run from an early morning class assignment.

In Table 9 we explore whether being assigned preceding courses before a class affects performance in future classes in the same subject area. Our results in Table 9 are consistent with our findings in Table 8. In column 1 in Panel A of Table 9 we find a small, but statistically insignificant, negative effect of preceding courses on future performance. However, including unique course fixed effects and demographic controls in columns 2-3 generate positive, but statistically insignificant, estimates of the effects of preceding courses on future performance. One caveat to our results in Table 9 is that our estimates of preceding courses on current performance are imprecise and smaller in magnitude than our estimates in Table 6, so these estimates should be interpreted more cautiously than those presented in in Table 8. Nevertheless, neither our results in Tables 8 nor 9 indicate that fatigue has persistent negative effects on performance. These results help rule out the possibility that our primary results are generated by a rational response to reduced performance.

[27]Subjects with multiple required courses include chemistry, English, math, and physics.

Given that our findings are unlikely to be driven by a rational response to increased fatigue, we finally turn to exploring our primary posited mechanism of attribution bias. In our conceptual framework, we identified that student's states in early morning courses could generate attribution bias through two primary channels. First, students may misattribute the negative effects of fatigue on performance to their subject-specific ability. Second, students may misattribute the unpleasantness of taking a course when fatigued to a lack of enjoyment of the subject. One way to explore whether our effects are coming through performance or some other channel, such as tastes, is by including course performance as a covariate in our estimates. In Table 10 we include controls for course performance in the specifications outlined in equations (1) and (2) to examine whether the effects of fatigue operate through the channel of performance or some other channel.[28] There are two important caveats to this approach. First, because course performance is endogenous, the estimates in these are no longer unbiased and should be interpreted cautiously. Second, even if the response to early morning courses is completely loading on performance this does not rule out other channels. For example, poor performance may be a result of a reduction of interest in the subject area. Nevertheless, we find that the results in Table 10 are suggestive that channels that rely on a response to performance are unlikely to fully explain our results. In columns 1-3 of Panel A we find that controlling for course performance reduces the absolute magnitude of our estimates of the effect of 7:30 AM courses on major choice by between 32% and 37% and makes our estimates statistically insignificant. In Panel B of Table 10 we find more compelling evidence that the effects of fatigue are not acting through a channel of reduced performance. After controlling for performance, we find in columns 1-3 of Table 10 that each additional preceding course reduces the probability that students major in a related course by between 6.73% and 10.78% (or between 0.14 and 0.21 percentage points), which is nearly identical to the range of effects found in our primary estimates shown in Table 4.

5.3 Alternate Mechanisms and Robustness Checks

An alternative explanation of our results is that poor performance in a required course could mechanically reduce the probability that students enroll in a corresponding major. While there are no formal performance standards to be admitted into a major at USMA, departments do have to approve an application to a major and have the discretion to reject an application. If departments have implicit grade standards in subject-area courses, then poor performance in a corresponding course might mechanically reduce the probability that students select a major. To address this potential concern we separate majors by the fraction of students

[28] Angrist et al. (2016) use the same approach to disentangle the crowd-in and crowd-out effects of a large grant program on other forms of student aid.

who receive worse than a 3.0 grade point (i.e. B average) in corresponding required courses and enroll in the major. Majors with low fractions of below 3.0 grade point students we designate as selective majors. If our effects are driven by selective majors, we may be concerned about a mechanical relationship between variation in course schedules and college major choice. However, in Appendix Table A.4 we show that there is no evidence that our results are driven by selective majors but find suggestive evidence that both the effects of early morning courses and number of preceding courses on major choice are primarily driven by courses with less selective admission patterns. These results suggest that the effects are not driven by grade cut-offs.

Another potential concern is that, in spite of balance across observable characteristics observed in Tables 2 and 3, unobserved selection into course schedules could be contributing to our results. Specifically, it is possible that students who have unobservable preferences for certain majors are able to arrange their schedules to have courses related to those majors at preferred times (i.e. times other than 7:30 AM and after breaks). To test for this type of selection, we take advantage of the fact that students take required courses in both semesters during their Sophomore year, but are required to declare a major during the first semester of their Sophomore year. If students are able to manipulate their schedules to get their major-related courses at preferred times, then it is plausible that our results could be driven by selection. We perform a falsification test that estimates the effect of having an early morning class or preceding courses in students' second semester of their sophomore year on their major choice, which is declared in their first semester of their sophomore year. If there is selection on unobservables, then results of this falsification test should be similar to our main results. The results of this test are reported in Table 11. We find no evidence that having either an early morning class (Panel A) or preceding courses (Panel B) in the semester after a student's college major decision affects a student's major choice. The effects for early morning are in fact in the opposite direction of the main effects, although statistically insignificant. The effects for preceding courses are in the same direction of the main effects, however much smaller and statistically insignificant, suggesting a limited scope for selection on unobservables to explain the results.[29]

We also run a number of robustness checks to test whether our results are driven by how we define our outcomes, how we define our treatments, and how we construct our sample. Specifically, in Appendix Table A.5 we re-estimate our primary specifications with a broader definition of corresponding majors (as outlined in Appendix Table A.1). In Appendix Table A.6 we exclude athletes from our primary specifications. In

[29]Because of a much smaller sample size (54,613 vs. 233,598), our estimates in Table 11 are significantly less precise than our primary estimates. Nevertheless, we believe that this falsification test is informative because the results in Panel A of Table 11 are opposite signed of the primary estimates in Panel A of Table 4 and the results in Panel B of Table 11 are less than half the magnitude of the primary estimates in Panel B of Table 4.

Appendix Table A.7, we simultaneously estimate the effects of being assigned to 7:30 AM, 8:40 AM, 11:00 AM, 1:55 PM and 3:05 PM courses (omitting the most commonly assigned course period of 9:40AM) on selecting a corresponding major. In Appendix Table A.8 we estimate equation (2), but replace our linear definition of preceding courses with an indicators for one, two, and three preceding courses.

Our estimates are robust to each of the approaches outlined above and generate a few notable patterns. In Appendix Table A.7, we find that while assignment to 7:30 AM courses reduces the probability that students major in a related subject, assignment to 11:00 AM courses *increases* the probability that students major in a course. In Appendix Table A.8 we find similar point estimates for one and two preceding courses on major selection (with the one period estimates being measured with more precision), but a much larger negative effect of three preceding courses. Our results, however, are not precise enough to rule out linear effects.

Finally, in Appendix Table A.9 we examine heterogeneity by student characteristics including sex, race, prior college experience, and academic aptitude. While we do not see consistent heterogeneous effects of fatigue across sex, race, or academic aptitude, we find that early morning courses and preceding courses have larger estimated effects on students without prior experience. While this result is consistent with the predictions of attribution bias, the differences between students with and without prior college experience are too imprecisely estimated to draw any certain conclusions.

6 Conclusion

This paper documents an attribution bias in the consequential domain of college major choice. We find that USMA students are less likely to enroll in a major if they are assigned to an early morning section of the corresponding introductory (general education) course. This result is consistent with students misattributing the negative effects of their temporary fatigue in the class to some fixed attribute of the overall subject. While the early morning course assignment does generate slightly diminished performance in the class itself, we show the overall effect is difficult to fully explain by a rational expectation of diminished performance in the corresponding major. Moreover, we show that this type of attribution bias also holds for a second, but related type of fatigue generated by course timings (back-to-back courses).

Our results have immediate policy implications. For example, an institution that would like to increase the number of majors in a particular subject may be able to do so at little or not cost by ensuring that the corresponding introductory course is offered after a break and outside of the early morning time-slot.

While it may seem that such policies are zero sum in the sense that one department's gain in majors will be another department's loss, this may not be the case. Given that many students in the US are on the margin of dropping out of college, it is possible that institutions could increase retention by minimizing fatigue across all introductory classes while students form their first impressions of fields.[30] Beyond scheduling, institutions may wish to shift other resources to their introductory courses (e.g. higher quality instructors), as this initial experience may have a large influence on major choice.

The findings of this paper also have implications that go beyond education policy. In prior work, Haggag et al. (2018) find evidence of attribution bias generated by temporary states of thirst and weather in the decisions of whether to consume a drink and return to an amusement park, respectively. Our evidence of attribution bias is generated by a different temporary state (fatigue) in a decision with much higher stakes (college major choice). The consistency of our findings with those of Haggag et al. (2018), in spite of the significant differences in contexts, suggest that the influence of attribution bias on decision making could be widespread.

[30]Source: https://nces.ed.gov/fastfacts/display.asp?id=40 accessed 10/12/2017

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Tables and Figures

Table 1: Summary Statistics for Cadets

	Mean	Std. Dev.	Min.	Max.	N
Female	0.165	0.371	0	1	18,753
Asian	0.072	0.258	0	1	18,753
Black	0.085	0.279	0	1	18,753
Hispanic	0.087	0.282	0	1	18,753
White	0.721	0.449	0	1	18,753
Prior Military Service	0.163	0.370	0	1	18,753
Prior College Attendance	0.220	0.414	0	1	18,753
USMA Preparatory Academy	0.149	0.356	0	1	18,753
Division I Athlete	0.332	0.471	0	1	18,753
Age	19.8	1.005	18	27	18,753
Average Number of Courses	5.14	0.265	2	6.5	18,753
SAT Verbal	639	73.4	300	800	18,753
SAT Math	652	68.4	390	800	18,753

Observations from students attending USMA between 2001 and 2017.

Table 2: Assignment to First Period Classes: Conditional Randomization Checks

	(1)	(2)	(3)	(4)	(5)
Female	0.0023*	0.0018	0.0018	-0.0001	-0.0002
	(0.0013)	(0.0012)	(0.0012)	(0.0013)	(0.0011)
Age	-0.0005	-0.0013*	-0.0013*	-0.0013**	-0.0012**
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)
Asian	-0.0015	-0.0005	-0.0005	-0.0009	0.0001
	(0.0020)	(0.0019)	(0.0020)	(0.0020)	(0.0018)
Black	-0.0055***	-0.0028	-0.0028	-0.0021	-0.0021
	(0.0020)	(0.0018)	(0.0018)	(0.0018)	(0.0016)
Hispanic	-0.0004	0.0018	0.0018	0.0015	0.0013
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0014)
SAT Verbal	0.0031***	0.0000	0.0000	-0.0002	-0.0006
	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0010)
SAT Math	-0.0049***	-0.0002	-0.0002	-0.0002	-0.0002
	(0.0016)	(0.0014)	(0.0014)	(0.0014)	(0.0013)
Academic Composite	-0.0031	-0.0000	-0.0001	0.0000	0.0004
	(0.0022)	(0.0018)	(0.0018)	(0.0018)	(0.0016)
Prior Service	-0.0014	0.0013	0.0013	0.0013	0.0021
	(0.0030)	(0.0028)	(0.0028)	(0.0028)	(0.0025)
Prior College	0.0009	0.0016	0.0016	0.0014	0.0012
	(0.0020)	(0.0019)	(0.0019)	(0.0019)	(0.0017)
USMA Preparatory School	-0.0039	-0.0040	-0.0040	-0.0027	-0.0028
	(0.0031)	(0.0029)	(0.0028)	(0.0028)	(0.0026)
N	233,598	233,598	233,598	233,598	233,598
R^2	0.0030	0.0321	0.2057	0.2058	0.2590
F-Stat P-Value	0.0000	0.1534	0.1769	0.5977	0.5275
Division I Athlete	N	Y	Y	N	N
Course Schedule FE	N	Y	Y	Y	Y
Course FE	N	N	Y	Y	Y
Sport x Semester FE	N	N	N	Y	Y
Faculty FE	N	N	N	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each specification represents results for a regression where the dependent variable is an indicator for first period. The SAT verbal, SAT math, and academic composite variables were divided by 100 prior to estimation. All specifications include a year fixed effects and Columns 2 and 3 include an indicator for being a recruited Division I athlete. The course roster fixed effect is a fixed effect for the particular combination of courses a student takes in a given semester (e.g. Calculus I, Economics, US History, and Physics). Robust standard errors are clustered at the individual and section-by-year levels.

Table 3: Number of Preceding Classes: Conditional Randomization Checks

	(1)	(2)	(3)	(4)	(5)
Female	0.0003	0.0006	0.0006	0.0014	0.0065**
	(0.0030)	(0.0030)	(0.0030)	(0.0032)	(0.0028)
Age	0.0004	-0.0002	-0.0002	-0.0002	-0.0008
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0013)
Asian	0.0044	0.0048	0.0048	0.0051	0.0053
	(0.0045)	(0.0046)	(0.0046)	(0.0046)	(0.0041)
Black	-0.0007	-0.0027	-0.0027	-0.0005	-0.0028
	(0.0043)	(0.0042)	(0.0042)	(0.0042)	(0.0036)
Hispanic	-0.0031	-0.0005	-0.0005	-0.0000	-0.0004
	(0.0039)	(0.0038)	(0.0038)	(0.0038)	(0.0034)
SAT Verbal	0.0014	-0.0027	-0.0027	-0.0024	-0.0016
	(0.0022)	(0.0024)	(0.0024)	(0.0024)	(0.0021)
SAT Math	0.0088***	0.0007	0.0007	0.0006	0.0001
	(0.0029)	(0.0028)	(0.0028)	(0.0028)	(0.0025)
Academic Composite	-0.0015	-0.0005	-0.0005	-0.0003	0.0030
	(0.0037)	(0.0037)	(0.0036)	(0.0037)	(0.0032)
Prior Service	-0.0068	0.0008	0.0008	0.0004	-0.0013
	(0.0054)	(0.0054)	(0.0053)	(0.0054)	(0.0045)
Prior College	0.0068*	-0.0010	-0.0010	-0.0010	0.0026
	(0.0035)	(0.0036)	(0.0036)	(0.0036)	(0.0030)
USMA Preparatory School	0.0033	0.0026	0.0026	0.0023	0.0028
	(0.0057)	(0.0058)	(0.0057)	(0.0058)	(0.0048)
N	233,598	233,598	233,598	233,598	233,598
R^2	0.0092	0.0864	0.1227	0.0868	0.5044
F-Stat P-Value	0.0212	0.9563	0.9546	0.9799	0.3956
Division I Athlete	N	Y	Y	N	N
Course Schedule FE	N	Y	Y	Y	Y
Course FE	N	N	Y	Y	Y
Sport x Term FE	N	N	N	Y	Y
Unique Course FE	N	N	N	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each specification represents results for a regression where the dependent variable is the number of immediately preceding courses. The SAT verbal, SAT math, and academic composite variables were divided by 100 prior to estimation. All specifications include a year fixed effects and Columns 2 and 3 include an indicator for being a recruited Division I athlete. The course roster fixed effect is a fixed effect for the particular combination of courses a student takes in a given semester (e.g. Calculus I, Economics, US History, and Physics). Unique courses are individual classroom observations (i.e. the interaction between instructor, semester, section, and course). Robust standard errors are clustered at the individual and section-by-year levels.

Table 4: Fatigue and Selection of Major in Subject Area

Panel A: Time of Day

	(1)	(2)	(3)
7:30 AM Course	-0.0019**	-0.0019**	-0.0019**
	(0.0009)	(0.0009)	(0.0009)
N	233,598	233,598	233,598
R^2	0.0649	0.0766	0.0768
Dependent Variable Mean	0.01905	0.01905	0.01905
Teacher FE	N	Y	Y
Demographic Controls	N	N	Y
Peer Demographic Controls	N	N	Y

Panel B: Number of Immediately Preceding Courses

	(1)	(2)	(3)
Number of Preceding Courses	-0.0015**	-0.0022***	-0.0022***
	(0.0007)	(0.0008)	(0.0008)
N	233,598	233,598	233,598
R^2	0.0650	0.1357	0.1359
Dependent Variable Mean	0.01905	0.01905	0.01905
Unique Course FE	N	Y	Y
Demographic Controls	N	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered by unique course and student in parentheses. All columns in Panel A and B include year fixed effects, course roster fixed effects, sport-by-semester fixed effects, and fixed effects for the number of courses in a day. All columns in Panel A include indicators for whether courses were immediately preceded by other courses. Column 1 of Panel B additionally includes course time fixed effects. Demographic variables include: indicators for sex, race/ethnicity, prior military service, prior college attendance, attendance at preparatory academy, and SAT verbal scores, SAT math scores, and overall pre-attendance student ranking. Unique courses are individual classroom observations (i.e. the interaction between instructor, semester, section, and course). Our reported sample size includes singleton observations that do not contribute to our identifying variation. If we omit these observations, our effective sample sizes are 231,592, 231,571, and 231,450 in columns 1-3 of Panel A and 231,548, 231,394, and 231,394 in columns 1-3 of Panel B.

Table 5: Benchmark Comparisons

	(1)	(2)	(3)	(4)
Female STEM Instructor for Female Student	0.0076**	–	–	–
	(0.0034)	–	–	–
Prior Instructor Evaluation	–	0.0019***	–	–
	–	(0.0007)	–	–
Own Instructor Evaluation	–	–	0.0070***	–
	–	–	(0.0005)	–
Normalized Grade	–	–	–	0.0134***
	–	–	–	(0.0004)
N	16,554	57,837	86,122	233,598
R^2	0.1877	0.1103	0.1058	0.0896
Year FE	Y	Y	Y	Y
Course Schedule X Athlete FE	Y	Y	Y	Y
Course FE	Y	Y	Y	Y

$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered by unique course and student in parentheses. All columns include year fixed effects, course roster fixed effects, sport-by-semester fixed effects, and fixed effects for the number of courses in a day. Demographic variables include: indicators for sex, race/ethnicity, prior military service, prior college attendance, attendance at preparatory academy, and SAT verbal scores, SAT math scores, and overall pre-attendance student ranking. Column 1 only includes female observations in required STEM courses. STEM course subjects in our sample include: chemistry, computer science, math, physical geography, and physics. Column 2 includes all observations from students assigned to an instructor that has prior instructor evaluations. Column 3 includes all observations from students that fill out a course-specific evaluation.

Table 6: Fatigue and Normalized Academic Performance

Panel A: Time of Day

	(1)	(2)	(3)
7:30 AM Course	-0.0492***	-0.0531***	-0.0531***
	(0.0089)	(0.0080)	(0.0080)
N	233,598	233,598	233,598
R^2	0.2290	0.2688	0.2688
Teacher FE	N	Y	Y
Demographic Controls	N	N	Y
Peer Demographic Controls	N	N	Y

Panel B: Number of Immediately Preceding Courses

	(1)	(2)	(3)
Number of Preceding Courses	-0.0170***	-0.0138***	-0.0138***
	(0.0047)	(0.0045)	(0.0045)
N	233,598	233,598	233,598
R^2	0.2293	0.3609	0.3609
Unique Course FE	N	Y	Y
Demographic Controls	N	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered by unique course and student in parentheses. All columns in Panel A and B include year fixed effects, course roster fixed effects, sport-by-semester fixed effects, and fixed effects for the number of courses in a day. All columns in Panel A also include indicators for whether courses were immediately preceded by other courses. Column 1 of Panel B additionally includes course time fixed effects. Demographic variables include: indicators for sex, race/ethnicity, prior military service, prior college attendance, attendance at preparatory academy, SAT verbal scores, SAT math scores, and overall pre-attendance student ranking. Unique courses are individual classroom observations (i.e. the interaction between instructor, semester, section, and course). Normalized academic performance measures an individual's distance in standard deviations from the course-by-semester mean performance. Our reported sample size includes singleton observations that do not contribute to our identifying variation. If we omit these observations, our effective sample sizes are 231,592, 231,571, and 231,450 in columns 1-3 of Panel A and 231,548, 231,394, and 231,394 in columns 1-3 of Panel B.

Table 7: Fatigue and Student Evaluations

	7:30 AM Courses			Immediately preceding courses		
	(1)	(2)	(3)	(4)	(5)	(6)
Aggregate Evaluations	-0.1392***	-0.1482***	-0.1468***	-0.0046	-0.0035	-0.0033
	(0.0129)	(0.0114)	(0.0112)	(0.0078)	(0.0077)	(0.0077)
Instructor Encouraged Responsibility	-0.0809***	-0.0854***	-0.0840***	-0.0070	0.0015	0.0016
	(0.0096)	(0.0092)	(0.0092)	(0.0068)	(0.0074)	(0.0074)
Instructor Effective	-0.1343***	-0.1501***	-0.1491***	-0.0071	-0.0032	-0.0027
	(0.0128)	(0.0110)	(0.0109)	(0.0076)	(0.0072)	(0.0072)
Instructor Cares	-0.1030***	-0.1125***	-0.1119***	-0.0034	-0.0060	-0.0057
	(0.0108)	(0.0098)	(0.0098)	(0.0073)	(0.0073)	(0.0073)
Instructor Respectful	-0.0740***	-0.0826***	-0.0820***	-0.0009	-0.0078	-0.0076
	(0.0111)	(0.0107)	(0.0107)	(0.0073)	(0.0074)	(0.0074)
Instructor Stimulating	-0.1372***	-0.1453***	-0.1441***	-0.0034	-0.0008	-0.0004
	(0.0120)	(0.0109)	(0.0107)	(0.0074)	(0.0074)	(0.0074)
Course Motivated Learning	-0.1206***	-0.1335***	-0.1325***	-0.0003	-0.0013	-0.0009
	(0.0117)	(0.0107)	(0.0105)	(0.0072)	(0.0075)	(0.0075)
Course Increased Critical Thinking	-0.0937***	-0.1046***	-0.1043***	0.0031	-0.0021	-0.0017
	(0.0128)	(0.0118)	(0.0118)	(0.0072)	(0.0076)	(0.0075)
Schedule Allows Reflection	-0.0742***	-0.0788***	-0.0778***	-0.0081	-0.0053	-0.0052
	(0.0111)	(0.0101)	(0.0099)	(0.0072)	(0.0080)	(0.0079)
Schedule Enables Max Performance	-0.0765***	-0.0804***	-0.0800***	-0.0093	-0.0066	-0.0065
	(0.0104)	(0.0099)	(0.0099)	(0.0072)	(0.0080)	(0.0080)
Peers Contribute to Learning	-0.0964***	-0.1029***	-0.1016***	-0.0050	-0.0039	-0.0037
	(0.0094)	(0.0095)	(0.0095)	(0.0068)	(0.0075)	(0.0075)
N	88,254	88,254	88,254	88,254	88,254	88,254
Teacher FE	N	Y	Y	N	–	–
Demographic Controls	N	N	Y	N	N	Y
Peer Demographic Controls	N	N	Y	N	–	–
Unique Course FE	–	–	–	N	Y	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each row/column entry reports the coefficient from a unique regression. Aggregate evaluations are a normalized sum of all the 5 point scores among 10 variables listed. Ratings from each individual question are converted from 5 point agreement scale questions to z-scores at the subject-year level. Observations come from student responses collected between 2008 and 2017. Aggregate evaluations, Schedule allows reflection, and Schedule enables max performance variables are not reported in 2008. Sample sizes for the other variables range between 100,076-100,830.

Table 8: Assignment to an Early Morning Class and Future Academic Performance

Panel A: Performance in Subsequent Subject Area Course			
	(1)	(2)	(3)
7:30 AM Course	0.0216*	0.0245**	0.0156*
	(0.0115)	(0.0106)	(0.0086)
N	81,958	81,958	81,958
R^2	0.2160	0.2390	0.2551
Panel B: Performance in Current Subject Area Course			
	(1)	(2)	(3)
7:30 AM Course	-0.0571***	-0.0637***	-0.0637***
	(0.0136)	(0.0120)	(0.0120)
N	81,958	81,958	81,958
R^2	0.2282	0.2809	0.2809
Teacher FE	N	Y	Y
Demographic Controls	N	N	Y
Peer Demographic Controls	N	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered by unique course and student in parentheses. For chemistry, English, math, and physics multiple courses are required. Panel B reports the effect of having an early morning course in the current semester on current performance in the subject (i.e. same semester normalized GPA in the subject). Panel A reports the effect of having an early morning course in the current semester on performance in the next course (i.e. next semester normalized GPA in the subject). All columns include year fixed effects, course roster fixed effects, sport-by-semester fixed effects, fixed effects for the number of courses in a day, and indicators for whether courses were immediately preceded by other courses. Demographic variables include: indicators for sex, race/ethnicity, prior military service, prior college attendance, attendance at preparatory academy, and SAT verbal scores, SAT math scores, and overall pre-attendance student ranking. Normalized academic performance measures an individual's distance in standard deviations from the course-by-semester mean performance.

Table 9: Number of Preceding Courses and Future Academic Performance

Panel A: Performance in Subsequent Subject Area Course			
	(1)	(2)	(3)
Number of Preceding Courses	-0.0012	0.0040	0.0040
	(0.0074)	(0.0077)	(0.0077)
N	81,925	81,925	81,925
R^2	0.2160	0.3257	0.3257
Panel B: Performance in Current Subject Area Course			
	(1)	(2)	(3)
Number of Preceding Courses	-0.0057	-0.0008	-0.0008
	(0.0060)	(0.0052)	(0.0052)
N	81,925	81,925	81,925
R^2	0.3039	0.4675	0.4675
Unique Course FE	N	Y	Y
Demographic Controls	N	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered by unique course and student in parentheses. For chemistry, English, math, and physics multiple courses are required. Panel B reports the effect of having a preceding course in the current semester on current performance in the subject (i.e. same semester normalized GPA in the subject). Panel A reports the effect of having a preceding course in the current semester on performance in the next course (i.e. next semester normalized GPA in the subject). All columns include year fixed effects, course roster fixed effects, sport-by-semester fixed effects, and fixed effects for the number of courses in a day. Column 1 additionally includes course time fixed effects. Demographic variables include: indicators for sex, race/ethnicity, prior military service, prior college attendance, attendance at preparatory academy, and SAT verbal scores, SAT math scores, and overall pre-attendance student ranking. Unique courses are individual classroom observations (i.e. the interaction between instructor, semester, section, and course). Normalized academic performance measures an individual's distance in standard deviations from the course-by-semester mean performance.

Table 10: Fatigue and Selection of Major in Subject Area, Controlling for Performance

Panel A: Time of Day

	(1)	(2)	(3)
7:30 AM Course	-0.0013	-0.0013	-0.0013
	(0.0009)	(0.0009)	(0.0009)
Normalized Grade	0.0121***	0.0122***	0.0122***
	(0.0004)	(0.0004)	(0.0004)
N	233,598	233,598	233,598
R^2	0.0712	0.0825	0.0825
Dependent Variable Mean	0.01905	0.01905	0.01905
Teacher FE	N	Y	Y
Demographic Controls	N	N	Y
Peer Demographic Controls	N	N	Y

Panel B: Number of Immediately Preceding Courses

	(1)	(2)	(3)
Number of Preceding Courses	-0.0013**	-0.0021***	-0.0021***
	(0.0007)	(0.0008)	(0.0008)
Normalized Grade	0.0121***	0.0130***	0.0130***
	(0.0004)	(0.0004)	(0.0004)
N	233,598	233,598	233,598
R^2	0.0711	0.1414	0.1414
Dependent Variable Mean	0.01905	0.01905	0.01905
Unique Course FE	N	Y	Y
Demographic Controls	N	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered by unique course and student in parentheses. All columns in Panel A and B include year fixed effects, course roster fixed effects, sport-by-semester fixed effects, and fixed effects for the number of courses in a day. All columns in Panel A also include indicators for whether courses were immediately preceded by other courses. Column 1 of Panel B additionally includes course time fixed effects. Demographic variables include: indicators for sex, race/ethnicity, prior military service, prior college attendance, attendance at preparatory academy, and SAT verbal scores, SAT math scores, and overall pre-attendance student ranking. Unique courses are individual classroom observations (i.e. the interaction between instructor, semester, section, and course). Our reported sample size includes singleton observations that do not contribute to our identifying variation. If we omit these observations, our effective sample sizes are 231,592, 231,571, and 231,450 in columns 1-3 of Panel A and 231,548, 231,394, and 231,394 in columns 1-3 of Panel B. Normalized academic performance measures an individual's distance in standard deviations from the course-by-semester mean performance.

Table 11: Falsification Test: Fatigue and Prior Major Choice

Panel A: Time of Day			
	(1)	(2)	(3)
7:30 AM Course	0.0014	0.0019	0.0019
	(0.0019)	(0.0019)	(0.0019)
N	54,613	54,613	54,613
R^2	0.2024	0.2184	0.2187
Dependent Variable Mean	0.0216	0.0216	0.0216
Teacher FE	N	Y	Y
Demographic Controls	N	N	Y
Peer Demographic Controls	N	N	Y

Panel B: Number of Immediately Preceding Courses			
	(1)	(2)	(3)
Number of Preceding Courses	-0.0005	-0.0008	-0.0008
	(0.0011)	(0.0011)	(0.0011)
N	54,613	54,613	54,613
R^2	0.2024	0.2953	0.2953
Dependent Variable Mean	0.0216	0.0216	0.0216
Unique Course FE	N	Y	Y
Demographic Controls	N	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered by unique course and student in parentheses. This table estimates the relationship between fourth semester variation in course schedules and third semester major choices. All columns in Panel A and B include year fixed effects, course roster fixed effects, sport-by-semester fixed effects, and fixed effects for the number of courses in a day. All columns in Panel A also include indicators for whether courses were immediately preceded by other courses. Column 1 of Panel B additionally includes course time fixed effects. Demographic variables include: indicators for sex, race/ethnicity, prior military service, prior college attendance, attendance at preparatory academy, and SAT verbal scores, SAT math scores, and overall pre-attendance student ranking. Unique courses are individual classroom observations (i.e. the interaction between instructor, semester, section, and course).

A Appendix

Table A.1: Mapping Between Required Courses and Majors

Course	Year	Majors (Narrow)	Fraction	Majors (Broad)	Fraction
Chemistry I	1	Chemistry	0.008	Chemistry; Chemical Engineering	0.019
Chemistry II	1	Chemistry	0.009	Chemistry; Chemical Engineering	0.020
English Composition	1	English	0.003	English; Art, Philosophy, and Literature	0.018
English Literature	1	English	0.003	English; Art, Philosophy, and Literature	0.020
US History	1	US History	0.017	US History; International History; Military History; European History	0.044
World History	1	International History	0.023	US History; International History; Military History; European History	0.052
Western Civilization	1	European History History	0.004	US History; International History; Military History; European History	0.053
Math Modeling	1	Mathematical Sciences	0.008	Mathematical Sciences	0.008
Calculus I	1	Mathematical Sciences	0.008	Mathematical Sciences	0.008
General Psychology	1	Psychology	0.024	Psychology; Engineering Psychology	0.042
Computing and Information Technology	1	Computer Science; Information Technology	0.041	Computer Science; Information Technology	0.041
Calculus II	2	Mathematical Sciences	0.008	Mathematical Sciences	0.008
Probability and Statistics	2	Mathematical Sciences	0.031	Mathematical Sciences	0.031
Physics	2	Physics	0.014	Physics; Physics Engineering; Interdisciplinary Physics	0.015
Economics	2	Economics	0.076	Economics	0.076
American Politics	2	Political Science	0.030	International Relations; Political Science	0.057
Philosophy and Ethics	2	Philosophy	0.002	Philosophy; Art, Philosophy, and Literature	0.021
Physical Geography	2	Geography	0.075	Geography	0.075

Because majors are selected during the third semester, only a subsample of students take the listed second year courses. History courses are not offered at 7:30 AM. As a result, history courses only contribute to the analysis variation in the preceding courses specifications. The Fraction column refers to the fraction of students in the course who eventually major in the corresponding major(s).

Table A.2: Early Morning Courses and Selection of Major in Subject Area

	(1)	(2)	(3)	(4)	(5)	(6)
7:30 AM Course	-0.0017**	-0.0022**	-0.0019**	-0.0019**	-0.0019**	-0.0019**
	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
N	233,598	233,598	233,598	233,598	233,598	233,598
R^2	0.0269	0.0270	0.0645	0.0762	0.0768	0.0768
Dependent Variable Mean	0.01905	0.01905	0.01905	0.01905	0.01905	0.01905
General schedule FE	N	Y	Y	Y	Y	Y
Specific schedule FE	N	N	Y	Y	Y	Y
Teacher FE	N	N	N	Y	Y	Y
Demographic Control	N	N	N	N	Y	Y
Peer Demographic Controls	N	N	N	N	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered by unique course and student in parentheses. All specifications include year and course fixed effects. General schedule fixed effects include an indicator for the number of courses a student has in a day and an indicator for the number of immediately preceding courses. The course roster fixed effect is a fixed effect for the particular combination of courses a student takes in a given semester (e.g. Calculus I, Economics, US History, and Physics). Demographic variables include: indicators for sex, race/ethnicity, prior military service, prior college attendance, attendance at preparatory academy, and SAT verbal scores, SAT math scores, athlete status, and overall pre-attendance student ranking. Our reported sample size includes singleton observations that do not contribute to our identifying variation. If we omit these observations, our effective sample sizes are 233,598, 233,598, 231,592, 231,571, 231,571, and 231,450 in columns 1-6, respectively.

Table A.3: Immediately Preceding Courses and Selection of Major in Subject Area

	(1)	(2)	(3)	(4)	(5)
Number of Preceding Courses	-0.0005	-0.0019***	-0.0015**	-0.0023***	-0.0022***
	(0.0006)	(0.0006)	(0.0007)	(0.0008)	(0.0008)
N	233,598	233,537	231,548	231,394	231,394
R^2	0.0269	0.0271	0.0647	0.1353	0.1359
Dependent Variable Mean	0.01905	0.01905	0.01905	0.01905	0.01905
General schedule FE	N	Y	Y	Y	Y
Specific Schedule FE	N	N	Y	Y	Y
Unique Course FE	N	N	N	Y	Y
Demographic Controls	N	N	N	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered by unique course and student in parentheses. All specifications include year and course fixed effects. General schedule fixed effects include an indicator for the scheduled course time (e.g. 7:30 AM, 8:40 AM,,3:05 PM) and the number of courses a student has that day. The course roster fixed effect is a fixed effect for the particular combination of courses a student takes in a given semester (e.g. Calculus I, Economics, US History, and Physics). Demographic variables include: indicators for sex, race/ethnicity, prior military service, prior college attendance, attendance at preparatory academy, and SAT verbal scores, SAT math scores, athlete status, and overall pre-attendance student ranking. Unique courses are individual classroom observations (i.e. the interaction between instructor, semester, section, and course). Our reported sample size includes singleton observations that do not contribute to our identifying variation. If we omit these observations, our effective sample sizes are 233,598, 233,537, 231,548, 231,394, and 231,394 in columns 1-5, respectively.

Table A.4: Fatigue and Selection of Major in Subject Area, Selective vs. Non-Selective Majors

Panel A: Time of Day

	(1)	(2)	(3)
7:30 AM Course	-0.0058**	-0.0045*	-0.0045*
	(0.0025)	(0.0024)	(0.0024)
7:30 AM*Selective Major	0.0050*	0.0033	0.0033
	(0.0026)	(0.0025)	(0.0025)
N	233,598	233,598	233,598
R^2	0.0649	0.0766	0.0766
Dependent Variable Mean	0.01905	0.01905	0.01905
Teacher FE	N	Y	Y
Demographic Controls	N	N	Y
Peer Demographic Controls	N	N	Y

Panel B: Number of Immediately Preceding Courses

	(1)	(2)	(3)
Number of Preceding Courses	-0.0023**	-0.0037***	-0.0037***
	(0.0011)	(0.0014)	(0.0014)
Preceding Courses*Selective Major	0.0013	0.0024	0.0024
	(0.0013)	(0.0016)	(0.0016)
N	233,598	233,598	233,598
R^2	0.0650	0.1357	0.1357
Dependent Variable Mean	0.01905	0.01905	0.01905
Unique Course FE	N	Y	Y
Demographic Controls	N	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered by unique course and student in parentheses. All columns in Panel A and B include year fixed effects, course roster fixed effects, sport-by-semester fixed effects, and fixed effects for the number of courses in a day. All columns in Panel A also include indicators for whether courses were immediately preceded by other courses. Column 1 of Panel B additionally includes course time fixed effects. Demographic variables include: indicators for sex, race/ethnicity, prior military service, prior college attendance, attendance at preparatory academy, and SAT verbal scores, SAT math scores, and overall pre-attendance student ranking. Unique courses are individual classroom observations (i.e. the interaction between instructor, semester, section, and course). Our reported sample size includes singleton observations that do not contribute to our identifying variation. If we omit these observations, our effective sample sizes are 231,592, 231,571, and 231,450 in columns 1-3 of Panel A and 231,548, 231,394, and 231,394 in columns 1-3 of Panel B.

Table A.5: Fatigue and Selection of a Broadly Defined Major in Subject Area

Panel A: Time of Day			
	(1)	(2)	(3)
7:30 AM Course	-0.0028***	-0.0024**	-0.0024**
	(0.0011)	(0.0010)	(0.0010)
N	233,598	233,598	233,598
R^2	0.0534	0.0655	0.0655
Dependent Variable Mean	0.03061	0.03061	0.03061
Teacher FE	N	Y	Y
Demographic Controls	N	N	Y
Peer Demographic Controls	N	N	Y

Panel B: Number of Immediately Preceding Courses			
	(1)	(2)	(3)
Number of Preceding Courses	-0.0005	-0.0020**	-0.0020**
	(0.0008)	(0.0009)	(0.0009)
N	233,598	233,598	233,598
R^2	0.0535	0.1278	0.1278
Dependent Variable Mean	0.03061	0.03061	0.03061
Unique Course FE	N	Y	Y
Demographic Controls	N	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered by unique course and student in parentheses. All columns in Panel A and B include year fixed effects, course roster fixed effects, sport-by-semester fixed effects, and fixed effects for the number of courses in a day. All columns in Panel A also include indicators for whether courses were immediately preceded by other courses. Column 1 of Panel B additionally includes course time fixed effects. Demographic variables include: indicators for sex, race/ethnicity, prior military service, prior college attendance, attendance at preparatory academy, and SAT verbal scores, SAT math scores, and overall pre-attendance student ranking. Unique courses are individual classroom observations (i.e. the interaction between instructor, semester, section, and course). Our reported sample size includes singleton observations that do not contribute to our identifying variation. If we omit these observations, our effective sample sizes are 231,592, 231,571, and 231,450 in columns 1-3 of Panel A and 231,548, 231,394, and 231,394 in columns 1-3 of Panel B.

Table A.6: Fatigue and Selection of Major in Subject Area, Excluding Athletes

Panel A: Timing

	(1)	(2)	(3)
7:30 AM Course	-0.0017	-0.0020*	-0.0020*
	(0.0011)	(0.0011)	(0.0011)
N	153,639	153,639	153,639
R^2	0.0714	0.0869	0.0869
Dependent Variable Mean	0.02015	0.02015	0.02015
Teacher FE	N	Y	Y
Demographic Controls	N	N	Y
Peer Demographic Controls	N	N	Y

Panel B: Number of Immediately Preceding Courses

	(1)	(2)	(3)
Number of Preceding Courses	-0.0008	-0.0017*	-0.0017*
	(0.0008)	(0.0010)	(0.0010)
N	153,608	153,608	153,608
R^2	0.0715	0.1708	0.1708
Dependent Variable Mean	0.02015	0.02015	0.02015
Unique Course FE	N	Y	Y
Demographic Controls	N	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered by unique course and student in parentheses. All columns in Panel A and B include year fixed effects, course roster fixed effects, sport-by-semester fixed effects, and fixed effects for the number of courses in a day. All columns in Panel A also include indicators for whether courses were immediately preceded by other courses. Column 1 of Panel B additionally includes course time fixed effects. Demographic variables include: indicators for sex, race/ethnicity, prior military service, prior college attendance, attendance at preparatory academy, and SAT verbal scores, SAT math scores, and overall pre-attendance student ranking. Unique courses are individual classroom observations (i.e. the interaction between instructor, semester, section, and course). Our reported sample size includes singleton observations that do not contribute to our identifying variation. If we omit these observations, our effective sample sizes are 231,592, 231,571, and 231,450 in columns 1-3 of Panel A and 231,548, 231,394, and 231,394 in columns 1-3 of Panel B.

Table A.7: Assignment to Early Morning Classes and Selection of Major in Subject Area

	(1)	(2)	(3)	(4)
7:30 AM Course	-0.0022**	-0.0019**	-0.0019**	-0.0019**
	(0.0010)	(0.0009)	(0.0009)	(0.0009)
8:40 AM Course	-0.0011	-0.0006	-0.0005	-0.0005
	(0.0013)	(0.0012)	(0.0012)	(0.0012)
11:00 AM Course	0.0027**	0.0027**	0.0027**	0.0027**
	(0.0012)	(0.0011)	(0.0011)	(0.0011)
1:55 PM Course	-0.0029**	-0.0016	-0.0015	-0.0015
	(0.0013)	(0.0014)	(0.0014)	(0.0014)
3:05 PM Course	-0.0003	0.0009	0.0009	0.0009
	(0.0015)	(0.0015)	(0.0015)	(0.0015)
N	233,598	233,598	233,598	233,598
R^2	0.0650	0.0766	0.0769	0.0769
Dependent Variable Mean	0.0190	0.0190	0.0190	0.0190
Teacher FE	N	Y	Y	Y
Demographic Controls	N	N	Y	Y
Peer Demographic Controls	N	N	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered by unique course and student in parentheses. Omitted hour is 9:50 AM. All columns include year fixed effects, course roster fixed effects, sport-by-semester fixed effects, fixed effects for the number of courses in a day, and indicators for whether courses were immediately preceded by other courses. Demographic variables include: indicators for sex, race/ethnicity, prior military service, prior college attendance, attendance at preparatory academy, and SAT verbal scores, SAT math scores, and overall pre-attendance student ranking.

Table A.8: Number of Preceding Courses and Selection of Major in Subject Area

	(1)	(2)	(3)
One Preceding Course	-0.0015	-0.0027**	-0.0027**
	(0.0009)	(0.0011)	(0.0011)
Two Preceding Courses	-0.0025	-0.0031	-0.0031
	(0.0017)	(0.0019)	(0.0019)
Three Preceding Courses	-0.0083*	-0.0119**	-0.0118**
	(0.0050)	(0.0058)	(0.0058)
N	233,598	233,598	233,598
R^2	0.0718	0.1428	0.1431
Dependent Variable Mean	0.0190	0.0190	0.0190
Unique Course FE	N	Y	Y
Demographic Controls	N	N	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered by unique course and student in parentheses. Each column includes year fixed effects, course roster fixed effects, sport-by-semester fixed effects, and fixed effects for the number of courses in a day. Additionally, column 1 includes course time fixed effects. Demographic variables include: indicators for sex, race/ethnicity, prior military service, prior college attendance, attendance at preparatory academy, and SAT verbal scores, SAT math scores, and overall pre-attendance student ranking. Unique courses are individual classroom observations (i.e. the interaction between instructor, semester, section, and course).

Table A.9: Heterogeneous Effects of Course Time on Student Major Selection

	(1)	(2)	(3)	(4)	(5)
Panel A: Time of Day					
7:30 AM Course	-0.0025***	-0.0014	-0.0022**	-0.0021*	-0.0049*
	(0.0009)	(0.0010)	(0.0009)	(0.0011)	(0.0029)
7:30 AM*Female	0.0037*	–	–	–	–
	(0.0022)				
7:30 AM*Minority	–	-0.0021	–	–	–
		(0.0016)			
7:30 AM*Prior College	–	–	0.0014	–	–
			(0.0018)		
7:30 AM*High SAT	–	–	–	0.0005	–
				(0.0015)	
7:30 AM*STEM	–	–	–	–	0.0039
					(0.0030)
R^2	0.039	0.039	0.039	0.039	0.039
N	233,598	233,598	233,598	233,598	233,598
Panel B: Number of Immediately Preceding Courses					
	(1)	(2)	(3)	(4)	(5)
Preceding Courses	-0.0058*	-0.0022**	-0.0026***	-0.0014	-0.0013
	(0.0030)	(0.0009)	(0.0008)	(0.0009)	(0.0011)
Preceding*Female	-0.0199***	–	–	–	–
	(0.0059)				
Preceding*Minority	–	-0.0003	–	–	
		(0.0012)			
Preceding*Prior College	–	–	0.0015	–	–
			(0.0013)		
Preceding*High SAT	–	–	–	-0.0017	–
				(0.0012)	
Preceding* STEM	–	–	–	–	-0.0015
					(0.0015)
R^2	0.462	0.041	0.041	0.041	0.041
N	233,598	233,598	233,598	233,598	233,598

Robust standard errors clustered by unique course and student in parentheses. All columns in Panel A and B include schedule fixed effects, D-1 athlete controls, and sport-by-term fixed effects, and controls for number of courses in a day. All columns in Panel A additionally include year fixed effects and indicators for whether courses were immediately preceded by other courses. Column 1 of Panel B includes course time fixed effects and year fixed effects. Unique courses are individual classroom observations (i.e. the interaction between: instructor x year x term x section x course). Our reported sample size includes singleton observations that do not contribute to our identifying variation. If we omit these observations, our effective sample sizes are and 231,450 in columns 1-5 of Panel A and 231,394 in columns 1-5 of Panel B.

Table A.10: Fatigue and Selection of Major in Subject Area, by Major Popularity

Panel A: Time of Day

	Low Popularity Majors	High Popularity Majors
7:30 AM Course	-0.0011	-0.0036
	(0.0007)	(0.0026)
N	154,391	73,462
R^2	0.0823	0.0952
Dependent Variable Mean	0.008	0.041
Teacher FE	Y	Y
Demographic Controls	Y	Y
Peer Demographic Controls	Y	Y

Panel B: Number of Preceding Courses

	Low Popularity Majors	High Popularity Majors
Number of Immediately Preceding Courses	-0.0003	-0.0049**
	(0.0006)	(0.0024)
N	154,333	73,454
R^2	0.1446	0.1522
Dependent Variable Mean	0.008	0.041
Unique Course FE	Y	Y
Demographic Controls	Y	Y

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered by unique course and student in parentheses. All columns in Panel A and B include year fixed effects course roster fixed effects, sport-by-semester fixed effects, and fixed effects for the number of courses in a day. All columns in Panel A also include indicators for whether courses were immediately preceded by other courses. Column 1 of Panel B additionally includes course time fixed effects. Demographic variables include: indicators for sex, race/ethnicity, prior military service, prior college attendance, attendance at preparatory academy, and SAT verbal scores, SAT math scores, and overall pre-attendance student ranking. Unique courses are individual classroom observations (i.e. the interaction between instructor, semester, section, and course).

Table A.11: Patterns in Course Schedules

		Number of Preceding Courses				
Period	Time	0	1	2	3	Totals
1	7:30-8:25 AM	43,676	–	–	–	43,676
2	8:40-9:35 AM	18,869	11,520	–	–	30,389
3	9:50-10:45 AM	36,427	9,322	6,360	–	52,109
4	11:00-11:15 AM	20,202	15,282	3,178	1,177	35,649
5	1:55-2:50 PM	35,649	–	–	–	35,649
6	3:05-4:00 PM	24,878	6,997	–	–	31,875
Totals		179,762	43,121	9,538	1,177	233,598

Observations at the student-course level. Observations are from students in first and second year core courses.