ANNENBERG
BROWN UNIVERSITY

EdWorkingPaper No. 24-937

How Early Morning Classes Change Academic Trajectories: Evidence from a Natural Experiment

Anthony LokTing Yim
Brigham Young University

Using a natural experiment which randomized class times to students, this study reveals that enrolling in early morning classes lowers students' course grades and the likelihood of future STEM course enrollment. There is a 79% reduction in pursuing the corresponding major and a 26% rise in choosing a lower-earning major, predominantly influenced by early morning STEM classes. To understand the mechanism, I conducted a survey of undergraduate students enrolled in an introductory course, some of whom were assigned to a 7:30 AM section. I find evidence of a decrease in human capital accumulation and learning quality for early morning sections.

VERSION: April 2024

Suggested citation: Yim, Anthony. (2024). How Early Morning Classes Change Academic Trajectories: Evidence from a Natural Experiment. (EdWorkingPaper: 24-937). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/7dwy-cq90

How Early Morning Classes Change Academic Trajectories: Evidence from a Natural Experiment*

Anthony LokTing Yim†

March 30, 2024

Abstract

Using a natural experiment which randomized class times to students, this study reveals that enrolling in early morning classes lowers students' course grades and the likelihood of future STEM course enrollment. There is a 79% reduction in pursuing the corresponding major and a 26% rise in choosing a lower-earning major, predominantly influenced by early morning STEM classes. To understand the mechanism, I conducted a survey of undergraduate students enrolled in an introductory course, some of whom were assigned to a 7:30 AM section. I find evidence of a decrease in human capital accumulation and learning quality for early morning sections.

Keywords: Higher Education, Human Capital, STEM, College Major

JEL Codes: I23, I26, D91

*I am grateful to my advisors Timothy Bond and Victoria Prowse for their support and encouragement at all stages of this project. I need to particularly thank Kevin Mumford for directing me to find the data and providing feedback in this project. I also thank Jillian Carr, Colin Sullivan, Brigham Frandsen, Jeff Denning, Rich Patterson, Kendall Kennedy, seminar participants at the Department of Economics from Brigham Young University and Purdue University, and participants at the AEFP, MEA, and BYU Graduate Student Conferences for their helpful comments. This study has been approved by the Purdue IRB (IRB-2021-1013 and IRB-2022-874) and has been registered (RCT ID: AEARCTR-0010038) at the AEA RCT Registry. All remaining errors are my own.

†Department of Economics, Brigham Young University, 2146 West View Building, Provo, UT 84602, USA; email: anthony_yim@byu.edu.

1 Introduction

A substantial body of research has shown early morning work schedules have negative effects on health and performance outcomes. Individuals who work in the early morning suffer from a higher rate of vehicle accidents and work-related injuries (Horne & Reyner, 1999; Nakata *et al.*, 2005; Barnes & Wagner, 2009), are more likely to have cardiovascular disease (Kecklund & Axelsson, 2016), experience slower reaction times (Van Den Berg & Neely, 2006), and have lower work productivity (Barnes & Wagner, 2009; Jagnani, 2018). Due to differences in circadian rhythm, young people are potentially even more at risk in early mornings (García *et al.*, 2012; Hasler *et al.*, 2014; Cosgrave *et al.*, 2018). Despite this, a substantial amount of education is conducted before 8:30 AM (Wolfson & Carskadon, 2005). The extent to which this educational scheduling decision detrimentally affects students' outcomes is still not well understood.

In this paper, I investigate the impact of early morning (7:30 AM) classes on some of the most important outcomes for post-secondary students: introductory grades, future STEM enrollment, persistence in challenging majors, and whether students graduate from higher-earning majors. To do this, I exploit a natural experiment at a large land-grant university which effectively randomized the course time for students. By using an instrumental variable approach and administrative data from the university, I find that being assigned to an early morning class causes a decrease in students' course grades by 0.06 GPA points, a 23% reduction in the probability of future STEM course enrollment, a 79% decline in the likelihood of studying in the corresponding major, and a 26% reduction in the probability to choose a major from the same college. In addition, having early morning classes raises the likelihood of graduating from a lower-earning major by 26%. The primary influence of graduating from a lower-earning major stems from being placed in early morning STEM classes.

While I find negative effects on academic performance, the magnitude is not strong enough to fully explain the change in enrollment and major selection behavior. To further investigate the mechanisms behind these changes, I conduct a survey of students in a large introductory economics course. My survey covers 343 students across both an early morning and mid morning section. I find students become less motivated and have lower participation in the early morning section. This suggests both academic and non-academic factors play an important role fueling the detrimental effect of early morning classes.

To the best of my knowledge, this is the first study to examine the impact of early morning classes on students' choice of majors with differing earning potentials. For college students, which majors and courses to select is an important decision since it directly influences students' academic trajectories and future labor market outcomes. Arcidiacono (2004) and Webber (2014a) document large earning gaps across majors due to ability sorting. Andrews *et al.* (2017) find long-lasting effects of major selection on earnings. Bleemer & Mehta (2022) provide strong evidence of huge earning premiums when students were selected into economics majors. Given the size of my estimates, my results suggest early morning class assignment can have durable detrimental effects on labor market outcomes.

Previous studies on the impact of early morning classes on college students' outcomes have been limited to military academies (Carrell *et al.*, 2011; Williams & Shapiro, 2018; Haggag *et al.*, 2021). While the unique environment of these institutions allows for clean identification, they are not representative of the typical university experience.[1] For instance, class attendance is mandatory in both military academies. Students who are not attentive in class face discipline from their commanding officers. In addition, students are required to participate in military drills before 7:30 AM on a typical day. Both academies set daily curfews and limit the ability of students to leave campus. Students are committed to five years of active-duty military service immediately after graduation, limiting the effects of major choice on career trajectories.

I find a similar effect on grades to the military academy studies, but much stronger

[1]According to the National Center for Education Statistics (NCES), the enrollment statistics at the university I study are similar to the enrollment statistics from other U.S. land-grant universities, such as gender ratio, racial composition, age group, SAT scores, etc.

effects on the choice of a major. This likely reflects the different institutional environment, as non-military students have more flexibility to respond to adverse conditions in their early educational experience. This study also opens up a potential channel where students may actually skip early morning classes since attendance is not mandatory in this land-grant university. Unlike my study, Haggag *et al.* (2021) are unable to investigate the effect of early morning classes on STEM persistence as there is limited course choice at the military academies and unable to address students' major selection associated with different earning potential, which may directly affect their labor market outcomes. In addition, Haggag *et al.* (2021) suggest attribution bias as a mechanism of their findings. In my paper, it means that students may misattribute the negative effects of early morning classes to the course subject, and I find suggestive evidence of attribution bias.

The rest of the paper proceeds as follows: Section Two discusses the biological background and the connection between sleep and educational outcomes, Section Three describes institutional setting and assignment algorithm, and Section Four explains the data and sample; Section Five discusses empirical strategy, and Section Six contains the results and mechanisms. Section Seven concludes.

2 Background

To understand how early morning classes affect students' decision making and educational outcomes, we first need to have a basic understanding of the circadian rhythm and the link between sleep and academic achievements.

2.1 The Circadian Rhythm

The circadian rhythm, a hard-wired "clock" in the brain that controls the production of the sleep-inducing hormone melatonin, is the biological rhythm that governs our sleep-wake cycles. During adolescence, teenagers experience significant changes of the circadian rhythm.

Hence, they experience more daytime sleepiness while preferring later bedtimes and wake-up times (Carskadon *et al.*, 1993; Wolfson & Carskadon, 1998; Crowley *et al.*, 2007). In fact, the average adolescent body starts producing melatonin at around 11 PM and continues in peak production until 7 AM, then stops its production at around 8 AM. In comparison, the highest production of melatonin for adults is at around 4 AM. Hence, if we ask teenagers to attentively participate in class activities at 7 AM , it is equivalent of asking adults to attend work meetings at 4 AM (Carrell *et al.*, 2011). In short, teenagers are more awake in the late morning and early evening, but they experience low levels of alertness in the early morning and mid-afternoon (Cardinali, 2008). A number of studies show that depending on the circadian rhythm of individuals, their ability to learn and receive information fluctuates throughout the day (Goldstein *et al.*, 2007; Schmidt *et al.*, 2007; Pope, 2016).

Standard university class schedules are incompatible with young students' circadian rhythms by requiring students to attend early morning classes when the melatonin generated by their bodies is at the peak levels.[2] With the current class schedules among many universities, students get up early to attend morning classes when they should be asleep.[3] I acknowledge other factors that contribute to later bedtimes, but studies show that young people stay awake mostly for biological reasons instead of social reasons (Carskadon *et al.*, 1993; Crowley *et al.*, 2007). The university class schedules, therefore, create an environment in which students learn less and make erroneous educational decisions, especially for students who are assigned to attend early morning classes.

[2]Policymakers and school administrators suggest that high schools and universities should start classes later. In fact, back in 2009, the House of Representatives introduced House Concurrent Resolution 176, also as known as the Zzz's to A's Resolution, which calls for secondary schools to begin school no earlier than 9 AM. However, this resolution is strictly voluntary, so schools and universities can still determine students' class schedules. In this study, I extend this issue to the university level because the majority of university freshmen are still in their late teen years when they first enroll in university courses.

[3]Students may potentially go to bed earlier on the night before the early morning classes, but it is difficult for them to do so because students' bodies do not start producing melatonin until late into the night.

2.2 The Relationship between Sleep and Academic Achievements

Mental states and sleep-wake cycles matter for learning (Persson *et al.*, 2007; Schmidt *et al.*, 2007; Williams & Shapiro, 2018). Early morning classes imply that students' biological sleep-wake cycle is disrupted (Carskadon *et al.*, 1993; Wolfson & Carskadon, 1998; Crowley *et al.*, 2007). Research finds that students who attend early morning classes receive lower test scores and course grades than other students from latter sections at the post-secondary level (Carrell *et al.*, 2011; Williams & Shapiro, 2018).[4]

In this study, I also explore the impact of early morning STEM courses on the probability of future enrollment in STEM courses and subsequent selection of majors. I am particularly interested in these outcomes because university administrators have increasingly focused on guiding students toward majors with higher earning potentials, particularly in STEM-related fields (Bleemer & Mehta, 2021; Sjoquist & Winters, 2015; Denning & Turley, 2017). In addition, the courses students undertake and their eventual majors significantly impact their long-term earnings and career paths (Chevalier, 2011; Altonji *et al.*, 2012; Hastings *et al.*, 2013; Altonji *et al.*, 2014; Kirkeboen *et al.*, 2016; Webber, 2014b; Patnaik *et al.*, 2020; Bleemer & Mehta, 2022). This paper demonstrates that early morning classes adversely affect students' future enrollment in STEM fields and reduce the likelihood of them selecting a corresponding major. Thus, it suggests that university course scheduling plays a significant role in shaping students' academic and labor market outcomes.

Consequently, students make important educational decisions, such as types of courses to take and majors to study, based on their perceived academic achievements within courses, such as test scores and final grades (Haggag *et al.*, 2021). Students may make improper academic decisions that have huge future labor market implications if they are subject to

[4] In K-12 literature, students earn higher grades with later school start times. For example, Edwards (2012) identifies a two percentile point gain in math test scores if students have later school start times due to variation in bus schedules from all middle schools in Wake County, North Carolina from 1999 to 2006. Additionally, Groen & Pabilonia (2019) show that when high schools start school days an hour later, female students have higher reading test scores, but they find no evidence for higher test scores from male students. Pope (2016) further investigates how the time of day affects students' productivity and concludes that having a morning instead of afternoon math or English class increases students' GPAs.

a disrupted mental state and fatigue while being exposed to academic subjects early in the morning.

3 Institutional Setting & Assignment Algorithm

3.1 Institutional Setting

Purdue is a large public university in the U.S. with a 2021 total enrollment of almost 50,000 students, including more than 37,000 undergraduate students. Purdue offers over 200 majors in agriculture, business management, education, engineering, science, social science, humanities, pharmacy, and veterinary medicine that students can freely choose from throughout their college career. In fact, more than 65% of undergraduate students studied in STEM-related fields in the academic year of 2021.[5] Like many public universities in the U.S., freshman students can declare a major in their first year at Purdue or also enroll in courses without a declared major.[6]

Courses and sections are two different concepts in this paper. While courses refer to a series of lectures or lessons in particular subjects, sections refer to specific times and locations that students are assigned to attend their particular courses.[7] Purdue offers multiple sections for various types of lower-level introductory courses throughout the day.

[5] 31% of undergraduate students are under the College of Engineering; 12% of them are in the College of Health and Human Science; 14% and 11% of undergraduate students are under the College of Science and Polytechnic Institute respectively. These four colleges are some of the most popular colleges in the university.

[6] Freshman and transfer students who have not chosen a major are assigned to exploratory studies, a 2-academic-year program to help students discover the major that best suits their interests. Nonetheless, students are free to leave the program within two years after they choose their major.

[7] For example, there is a course called ECON 101 with two different sections : section 1 at 7:30 AM and section 2 at 11:30 AM, so sections are the subsets of a course.

3.2 Course Assignment Algorithm

The Purdue class assignment algorithm is called the batch registration, which was reintroduced in 2018.[8] The university randomly assigns class schedules to undergraduate students through this algorithm conditional on their course request preferences.[9] The algorithm incorporates the individual course preference rankings as inputs to produce schedules for all students.[10] The algorithm assigns students in random order based on the number of available sections of each course students submit before assigning sections to students. Afterwards, those without a complete course schedule would be put in random order, and the algorithm assigns sections to them again(Müller & Murray, 2010).

Under the batch registration process, students request their preferred schedules as if they are entering one huge scheduling competition. Since students do not usually know how other students make their respective course requests and do not know the most optimal course request strategies, students submit their course requests in the hope that they receive their most preferred schedule.[11] Course characteristics (e.g., time, date, teacher's race, teacher's gender, etc.) are available on the university web page, and students can review them before

[8] Purdue University had been assigning class schedules to students via the batch registration for a long period of time, but it was discontinued in 2008. Between Fall 2008 and Spring 2018, students self registered for their courses as long as they met course prerequisites.

[9] The batch registration only applies to students enrolled in fall and spring terms. Even though Purdue provides summer sessions from May to early August, the batch registration process is not used, so class schedules are not randomly assigned to students. Instead, students just need to register for their preferred courses. Summer sessions usually start in the middle of May and end at the beginning of August. Like many other universities, the enrollment at Purdue is relatively lower in summer terms than the enrollment in fall and spring terms. The university offers fewer in-person courses and more online courses during summer.

[10] The batch registration optimizes the objective to satisfy students' course request preferences subject to the number of courses and sections the university offers, classroom capacity, and physical distances between classes. Students with similar course requests are grouped together. Then, the algorithm works in 6 phases: 1) The algorithm orders students based on the number of sections available for the courses they requested and assigns course sections to them. 2) Students without a complete schedule are taken in random order and are assigned sections. 3) The algorithm randomly selects and assigns an unassigned section to students. 4) The algorithm improves the overall schedules by using backtracking technique. 5) Students are selected randomly and try to fill in any available sections at that point if all their requests are unassigned. 6) The algorithm goes back to step 1 and starts over again. More discussion can be found under Appendix - Batch Registration.

[11] Even though students may potentially game the course assignment algorithm, they still need to compete with other students who also game the algorithm.

submitting their course request.[12] However, most freshman students do not state their preferred class times because they are unaware of this feature in the course request form. I will discuss more about course and section compliance rates in a later section.

4 Data and Sample

Data for this study comes from Purdue University in West Lafayette, Indiana, and includes 9,030 student-by-course-by-term observations from Fall 2018, Fall 2019, and Spring 2020.[13] I focus on domestic non-athlete students who are assigned to general education or introductory courses with multiple sections including at least one early morning class.

I split the data in two ways.[14] Hence, I can estimate students' likelihood to take STEM courses within the subsequent two terms for 5,118 student-course observations from Fall 2018, Fall 2019, and Spring 2020.[15] In terms of students' choice of major, I mainly focus on the domestic freshman students from Fall 2018, with 3,912 student-course observations, because they are going to be the first graduating class since the introduction of the class schedule randomization policy at Purdue University.[16]

Table 1 shows the descriptive statistics for my regression sample. Among all three panels, there are roughly 20% of student-course observations assigned to early morning classes.

[12]For time and date-related studies, please see Dills & Hernandez-Julian (2008), Carrell *et al.* (2011), Edwards (2012), Pope (2016), Diette & Raghav (2017), Williams & Shapiro (2018), Groen & Pabilonia (2019), and Haggag *et al.* (2021). For teacher's gender and race-related studies, please see Canes-Wrone & Rosen (1994), Robst *et al.* (1998), Robb & Robb (1999), Carrell *et al.* (2009), Hoffmann & Oreopoulos (2009), Ehrenberg & Brewer (1995), Ehrenberg *et al.* (1995), Rask & Bailey (2002), Dee (2004), Dee (2005), Klopfenstein (2005), and Price (2010). Even though Diette & Raghav (2017) investigate the impact of different class times on students' test scores at a private liberal art college, they do not test if the class assignments are random, so it casts doubt on the validation of the identification strategy.

[13]There are 9,020 student-course observations for estimating the effect on course grades. This number is lower than the reported observations of 9,030 since 10 of the student-course observations were not rewarded with a letter grade.

[14]Since I can observe more students' course taking information in multiple terms, I define this set of sample as "STEM Sample" that includes domestic non-athlete freshman students between the age of 18 and 21 years old from Fall 2018 to Spring 2020. Because I can only observe students' whole university career from the Fall 2018 cohort, I define "Major Sample" as domestic non-athlete freshman students between the age of 18 and 21 years old from Fall 2018.

[15]The data of Spring 2019 are excluded because Purdue did not randomly assign students class schedules.

[16]Samples in this study are all domestic non-athlete freshman students from the age of 18 to 21 years old.

There are more female students assigned in early morning sections than male students. Black, Hispanic, and "Other" students make up about 12% of the regression sample, with the majority of students being white.[17] In this study, I only include observations of domestic students in my main analysis because I can make the closest comparison with the findings of Carrell *et al.* (2011), Williams & Shapiro (2018), and Haggag *et al.* (2021).[18]

4.1 Course Request Data

My primary sources for students' academic schedules are the course request data from Fall 2018, Fall 2019, and Spring 2020 terms.[19] In this data set, I have course request information that students submit to the university before they receive their random class schedules including, the number of requested courses, order of requested courses, alternative courses (if requested courses are not granted to students), indicators of preferred class times, and indicators of required class times.[20] Figure A.1 in the appendix illustrates the course request form each undergraduate student needs to fill out.

After submitting course requests to the university, students receive their initial course assignments from the university on Batch Day. Students may not get the requested courses and times they prefer. Hence, the university allows them to adjust their course schedules by adding, dropping, and switching into different courses or class times before the add/drop deadline, which is four weeks into a term. After the add/drop deadline, the schedules become finalized, but students can still withdraw from courses with withdrawal records on their transcripts. The final grade of each course is recorded after all final exams and projects

[17] I identify Native Americans or undisclosed race as "Other" and include Pacific Islanders in the "Asians" category.

[18] Observations of Carrell *et al.* (2011), Williams & Shapiro (2018), and Haggag *et al.* (2021) are on students from the the USMA and USAFA who are all U.S. citizens.

[19] I exclude student observations from Fall 2020 and Spring 2021 because the university moved most of the classes to hybrid or online models to encounter the global Pandemic of COVID-19. Under the hybrid and online models, professors recorded lectures and allowed students to review them online, so students did not have to attend classes during the designated class time.

[20] The major difference between preferred and required class times is that students can list their preferred class times, but students can only state their required class times after approval from their academic advisors.

are concluded.[21]

To summarize course registration activities at Purdue, Figure 1 and the following bullet points illustrate the chronological order of course registration in a term:

- *BOR*: Beginning of course request registrations.
- *Batch Day*: Students receive their initial course assignments on that day, and it usually happens a month before the start of a term.
- *BOS*: Beginning of term.
- *A/D Deadline*: Students can freely add, drop, or change their class schedules before that day. This date is usually a week after the beginning of a term.
- *Term End*: The end of a term.
- *Period 1*: Students submit course requests.
- *Period 2*: Students can freely add, drop, or switch their classes without additional fee or marks on their transcripts.
- *Period 3*: Students can withdraw courses, but the withdrawals are shown in students' transcripts.

With the course request data available, I am able to estimate the causal effect of early morning classes on students' education outcomes by linking it with the course request data and registrar data.

4.2 Registrar Data

I observe several key pieces of students' information on educational outcomes, including final course grades and their majors by term, from the registrar data. Unlike the course

[21] Notice that not all students receive traditional course letter grades on a 4.0 scale. Instead, a low number of students receive pass or fail grade upon their completion of courses.

request data, the registrar data also include information on students' finalized class schedules, students' credit hours earned, age, gender, race, SAT scores, and first-generation student status. In addition, I linked the university-provided earning data for each college major with the respective majors students graduated from. This earning information for each college major was provided from Purdue's Center for Career Opportunities (CCO), where university alumni completed career surveys detailing their post-graduation employment status and income. I, then, calculated the average and median earnings for each major.

5 Empirical Strategy

I exploit a natural experiment at Purdue University. The identification strategy comes from the random class assignments conditional on student's course request preferences. This allows me to compare the effects of early morning classes on students' academic outcomes when students take the same course with the same instructor but in two different class times (i.e. 7:30 AM and 11:30 AM).[22] I focus on whether students are assigned to attend 7:30 AM classes as my instrument since 7:30 AM classes are the earliest lecture classes offered at Purdue. Even though instructor assignments to teach classes are not random, I include course-by-instructor-by-term level in my main specifications because the identification strategy is to compare students who take the same course with the same instructor but in either a 7:30 AM class or a non-7:30 AM class.

I will further discuss the empirical strategy in three subsections: course compliance, randomization, and instrumental variable.

[22]The course-by-instructor observations provide a way to control the endogeneity of instructor effect since assignments of instructors' teaching schedules are not exogenous. Senior or more popular faculty may teach classes in the late morning or in the afternoon, while junior faculty are likely to give lectures in the early morning.

5.1 Course Compliance

Figure 3 displays descriptive comparisons between early morning and non-early morning assignments. 1,749 student-course-term observations were assigned to early morning sections. 188 early morning assignments were dropped while 1,397 of them were kept to the early morning assignments. In addition, 164 student-course-term observations were switched into non-early morning sections. On the other hand, of those 9,795 observations who got assigned to non-early morning sections, 1,035 of them were dropped, and 1,452 observations were switched into early morning sections. Figure 3 shows that most students complied with the assignments they received with roughly 90% compliance rate.

Students can freely change their class schedules after the Batch Day, so there could be differential attrition between the treatment (7:30 AM classes) and control (non-7:30 AM classes) groups that may raise bias in this study. Table A.1 summarizes course compliance rates of the sample.[23] In Table A.1, the upper panel called "STEM Sample" displays the compliance rates for domestic non-athlete freshman students between the ages of 18 and 21 years old from Fall 2018 to Spring 2020, while the lower panel called "Major Sample" shows the compliance rates from Fall 2018.[24] In the upper panel, compliance rates of early morning and non-early morning sections show small mean differences. Even though the mean difference of "STEM" is 1.90% significant at the 10% level. Similarly, the mean difference of the lower panel is 0.419% and not statistically significant, so the differential attrition of this study is small and should not cause major issues.

5.2 Randomization

I examine how early morning classes affect students' educational trajectories by adopting instrumental variables (IV) estimation. Broadly speaking, ordinary least squares regressions

[23] The observations are in course-by-instructor-by-term level because the identification strategy is to compare students who take the same course with the same instructor but in either a 7:30 AM class or a non-7:30 AM class.

[24] In the following analyses, I will conduct different regression analyses by using observations from "STEM Sample" and "Major Sample."

of education outcomes on finalized class assignments are likely to yield biased estimates because of self-selection of class times. Purdue's conditionally random class assignments provide me with an approach to solve the endogeneity problem.

One key assumption is that assignments to early morning classes are random conditional on students' course request information. To test this, I regress an indicating variable for whether students are assigned into early morning classes on a vector of students' observable characteristics, including gender, race, standardized SAT scores, and first generation status conditional on course-by-term fixed effect and course request preferences.[25]

Table 2 shows the results from the regressions. In column 1, I regress indicators of assigned 7:30 AM classes on students' observable characteristics without course request controls and course-by-instructor-by-term fixed effect. Even though 3/8 of the characteristics differ at the 5% and 10% levels of significance, the observable characteristics of students are balanced across early morning and other period classes with the F-test p-value of 0.129. When I include course-by-instructor-by-term fixed effect in column 2, the students' observables are also balanced with no characteristics varying between early morning and non-early morning classes at the 5% level of significance. The joint F-test p-value is 0.134. After including both course-by-instructor-by-term fixed effect, course preference controls, and number of courses requested fixed effect in column 3, the joint F-test p-value of students' observable covariates increases to 0.23.[26] Altogether, columns 1, 2, and 3 of Table 2 suggest that students' assignments to early morning classes are conditionally random with F-test p-values greater than 0.1.

The course request preferences include information such as the number of requested courses, rank of requested courses, alternative courses (if requested courses are not granted to students), indicators of preferred class times (that are 7:30 AM or non-7:30 AM), and

[25]This approach is similar to the methods used by Carrell *et al.* (2011) and Haggag *et al.* (2021).

[26]Since my specifications of the balance test should be as close to the treatment level as possible, I use course-by-instructor-by-term fixed effect instead of course-by-term fixed effect even though the randomization occurs at the course level across terms. The results of these alternative specifications are shown in Table A.2, and the results are well-balanced.

indicators of required class times (that are 7:30 AM or non-7:30 AM).[27]

5.3 Instrumental Variable

If I estimate the effect of early morning classes by simply regressing my outcomes of interest on an indicator for whether students actually enroll in early morning classes shown in equation (1), the estimated results would be biased due to students' self-selection in or out of early morning classes. Therefore, I use an indicator for whether students get randomly assigned into early morning classes as the instrument.[28] Then, I estimate the following equation to identify the causal effects of early morning classes on educational outcomes by using the 2-stage-least square (2SLS) approach:

$$Y_{icpt} = \beta_0 + \beta_1 \mathit{Finalized\ Early}_{icpt} + \beta_2 S_i + \beta_3 C_{ict} + \sigma_{cpt} + \varepsilon_{icpt} \tag{1}$$

where Y_{icpt} indicates the education outcomes of students. $\mathit{Finalized\ Early}_{icpt}$ is an endogenous regressor and an indicator for whether student i in course c with instructor p at term t enrolls in an early morning class. S_i is a vector of students' observable characteristics, including gender, race, standardized SAT scores, first generation status, and college athlete status. C_{ict} is a vector of course request information students submit to the university before they receive their random class schedules including: number of requested courses, rank of requested courses, alternative courses if requested courses are not granted to students, indicators of preferred class times, and indicators of required class times. σ_{cpt} is the course-by-instructor-by-term fixed effect, which allows me to compare the effects of early morning classes and non-early morning classes taught by the same instructor in the same term. An indicating variable for whether students get randomly assigned to early morning classes $\mathit{Assigned\ Early}_{icpt}$ is the instrumental variable in this study.

[27] All course request controls are indicator variables. I also explicitly state that what class times students request and create different interaction terms between each course request control variable. Estimated results of both specifications are similar.

[28] I discuss the identification assumptions of this instrumental variable and the first stage regression model in Appendix III Regression Models.

Although students are not all compliers of the early morning class treatment, over 84% of course-by-instructor-by-term course assignments remain unchanged when I compare the compliance rates. For this purpose, I run a reduced form (or direct) regression model:

$$Y_{icpt} = \alpha_0 + \alpha_1 Assigned\ Early_{icpt} + \alpha_2 S_i + \alpha_3 C_{ict} + \sigma_{cpt} + \epsilon_{icpt} \tag{2}$$

where $Assigned\ Early_{icpt}$, the instrument, indicates whether students get randomly assigned to early morning classes. The subscript notations and definitions of other variables are consistent with the descriptions from equation (1).

As noted in equation (1), Y_{icpt} is students' education outcomes defined as follows:[29]

1. *Final Course Grades*

   Students receive their final course letter grades at the end of the term. The letter grades are on a 4.0 GPA scale. This variable of interest is a starting point to investigate the effect of early morning classes on students' human capital accumulation.[30] This indication of aptitude could also serve as a mechanism of students' course-taking behavior and major choice.

2. *Indicators for whether students are going to take corresponding STEM classes within the next two terms*

   STEM classes are defined as courses that are offered by departments with STEM affiliation. Departments with STEM affiliation refer to departments that offer STEM majors to undergraduate students. The U.S. Department of Homeland Security (DHS) STEM Designated Degree Program List is a complete list of fields of study that are STEM-verified by DHS for purposes of the 24-month STEM optional practical training (OPT) extension. University administrators and faculty then decide if majors

[29] Table **??** shows the lower-level division courses with multiple sections including at least one early morning section in each sample. Those courses are diversely offered by School of Science, Business School, School of Liberal Arts, and so on.

[30] Instructors may adjust final course grades for students and therefore creates measurement error. Yet, it is still the most relevant variable to infer their learning.

offered by different colleges are perceived as STEM respectively based on the intensity of science, technology, engineering, or mathematics courses and academic credits that each field of study requires.[31] Estimating whether students are likely to take corresponding STEM classes in subsequent terms projects their human capital development during their university career. It also infers how persistent students are in acquiring STEM-related skills. Since university graduates with strong STEM training have higher earnings than students with fewer STEM skills do, this estimation may shed more light on students' labor market outcomes in the future.

3. *Indicators for whether students are going to study in a major directly corresponding to the assigned early morning classes at 7:30 AM*

   The third outcome variable of interest is an indicator of whether students would study in a corresponding major and choose a major from the same college. I do so by creating a mapping between courses with multiple class times including at least one 7:30 AM classes and their most direct major.[32] For example, if a student gets assigned into a 100-level Principles of Economics course at 7:30 AM, I am interested in understanding if she will major in economics in the near future conditional on course request controls, student's observable characteristics, and course-by-instructor-by-term fixed effect.[33] Followed by Haggag *et al.* (2021), I also propose a broader level of mapping between courses and colleges in Table A.5.

4. *Indicators for whether students are going to graduate from a lower-earning major*

   Another outcome variable of interest is an indicator of whether a student is going to graduate from a lower-earning major. The indicator is 1 if he graduates from a

[31] Interested readers can go to the following website to view the STEM Designated Degree Program List associated with the Classification of Instructional Programs (CIP) codes by the U.S. Department of Education's National Center for Education Statistics (NCES).

[32] Table A.4 in the appendix shows the detailed mapping between courses and majors.

[33] A direct definition of the course-to-major mapping allows an education outcome as close to the level of treatment as possible. This approach also makes a more direct test for a possible mechanism, attribution bias.

lower-earning major, and zero otherwise. I categorize majors with earnings in the first quartile (Q1) as lower-earning majors. Initially, I link major earning data with the specific majors from which students graduate provided by Purdue's CCO. Following that, I rank these earnings and divide them into different quartiles: first (Q1), second (Q2), and third (Q3).

In Table 3, I estimate the first-stage regression. The instrument is unsurprisingly strong with an F-statistics over 940 in each column from both upper and lower panels.

6 Results and Mechanisms

6.1 The Effect on Academic Performance

First, I estimate whether students' final course grades are affected by assigned early morning classes in Table 4 by 2SLS and reduced form estimations of equation 1.[34] I find that students receive lower course grades if early morning classes are assigned to them by both 2SLS and reduced form estimations. In column (1), with the course-by-instructor-by-term fixed effect, assignments to early morning classes reduce performance by 0.0806 GPA points.[35]

The course-by-instructor-by-term fixed effect is the most credible identification strategy to explore the effects of early morning classes because it enables me to compare the effects on students from early morning and non-early morning sections within the same courses taught by the same instructors. When I include course request preferences such as the number of requested courses, ranks of requested courses, indicators of preferred class times, and indicators of requested class times in column (2), the estimates are still negative and

[34]I estimate the regression models by using only domestic undergraduate non-athlete students between the age of 18 and 21 years old because I am interested in studying how early morning classes affect traditional domestic freshman students who are in their late teen years. Also, the estimates can have more direct comparisons with the estimated results of Carrell *et al.* (2011), Williams & Shapiro (2018), and Haggag *et al.* (2021). Robust standard errors are clustered at the individual and section-by-term levels. Conventionally, clustering a higher level such as course-by-term level is more ideal. However, I do not have sufficient number course-by-term clustering with only 15.

[35]I only interpret estimated results from the 2SLS estimations for simplicity.

close with the p-value at 0.106. In column (3), the precision of my estimates increases after including demographic characteristics of students such as gender, race, first generation status, and standardized SAT scores. The estimated result in column (3) is 0.0598 significant at the 5% level with the magnitude slightly higher than the findings of Carrell *et al.* (2011), Williams & Shapiro (2018), and Haggag *et al.* (2021).[36] Altogether, my results in Table 4 provide evidence that early morning classes reduce students' academic performance.

Some STEM majors require a minimum GPA or course grade threshold, so students with lower course grades may shy away from taking more STEM classes and choosing a related major. Table 5 demonstrates a breakdown of the effect of early morning classes on each letter grade. I find suggestive evidence that early morning classes decrease the probability of getting higher grades especially with A-, Bs, and C+ from columns (2) to (6). In order to get admitted into the selective programs, students must reach a minimum GPA (3.0 or above) of required introductory courses. Assignments to early morning classes, therefore, inadvertently lower the chance for the marginal students to get into selective programs.

To understand the mechanisms of the findings, I conducted an online field survey by asking students about their in-class experiences from both early morning and non-early morning sections. The survey was distributed to students from a lower-level introductory economics course with two sections (7:30 AM and 9:30 AM) taught by the same instructor at Purdue University in Fall 2022.[37] The response rate was 0.409 with 343 respondents. 38% of students who responded to the survey came from the early morning section while 45% of other respondents came from the non-early morning section. Among the respondents, 0.51 of them were assigned to the 7:30 AM section, while 0.49 of them got assigned to the later section.[38] The response rates of students who got assigned to both sections are balanced, so

[36] I regress standardized course GPA on assigned early morning classes with the same specifications for the purpose of making direct comparisons with the findings of Carrell *et al.* (2011), Williams & Shapiro (2018), and Haggag *et al.* (2021).

[37] The survey has been approved by the Purdue IRB (IRB-2022-874). The survey is anonymous and strictly voluntary and does not affect any grades in this course. Upon completion of the survey, students can choose to enter a raffle to win a $5 Amazon gift card.

[38] Figure 2 shows compliance comparisons among two sections.

differential attrition is not a concern. In my survey, I listed 11 statements and asked them to choose one of the following responses: 1. Strongly Disagree, 2. Disagree, 3. Neither Agree or Disagree, 4. Agree, and 5. Strongly Agree.[39] Then, I regressed the survey outcomes of interest on assigned early morning classes in the following model:

$$F_i = \delta_0 + \delta_1 Assigned\ Early_i + \delta_2 C_i + \tau_i + \varepsilon_i \tag{3}$$

where F_i is an indicator for answering "Strongly Agree" or "Agree" in student i since the outcome variables are ordinally measured and are hard to interpret estimated results for if only using response values. τ_i is the class year rank fixed effect, and the definitions of other variables are consistent with previous equations. From columns (1) to (5) of Panel 1 in Table 6, the estimated results are related to students' in-class learning. I find suggestive evidence that students participate less in class discussions and do not think that early morning classes motivate learning. Students also conclude that they would learn more from a later section with the same instructor. The survey results are consistent with the findings of Tables 4 and 5, which suggest that early morning classes lower academic performance.[40]

Teaching quality may serve as another possible explanation. Instructors who teach multiple sections within the same course may teach with greater clarity in non-early morning classes because they have already given the same lecture in the morning and know in advance if the lectures are well-received by students. Then, instructors can adjust the lectures accordingly. However, in Table 7, I regress final course grades on an indicator for whether students are randomly assigned into subsequent classes taught by the same instructors within the same courses. It means that courses with multiple sections offered in the non-early morning period, late in the morning or in the afternoon would be included in this analysis because I want to test if students actually performed better academically in the subsequent section. The results of Table 7 show no evidence that being assigned into subsequent classes may

[39] Please see Appendix II for the entire student survey and Appendix IV for the summary statistics.
[40] Table A.9 shows the consistent results for only freshman students.

increase students' course grades.[41] Additionally, survey results from columns (1) to (4) of Panel 2 in Table 6 show no evidence about teaching quality in subsequent classes by same instructors.

Both estimated and survey results suggest that students' human capital accumulation is negatively affected by early morning classes. These findings may affect students' educational decisions in the future.

Exclusion restriction would be violated if taking an early morning class affects students' performance in other courses. To test this, I first calculate the leave-one-out term GPA excluding the course grade from the assigned early morning classes. Then, I regress the leave-one-out term GPA on an indicator for whether students were assigned to an early morning class with the same specification in equation (2). I find no evidence that attending early morning classes affect academic performances in other courses in Table 8.[42]

6.2 The Effect on Educational Decisions

6.2.1 The Propensity to Take Additional Corresponding STEM Courses

In Table 9, I estimate equations (1) and (2) on the impact of early morning classes on students' propensity to take corresponding STEM courses within the next two terms. Both the upper and lower panels of Table 9 present the results of the 2SLS and reduced form estimations, respectively.

In Table 9, column (1) is the standard regression with the course-by-instructor-by-term fixed effect because this enables me to estimate the effect of early morning sections within the same course taught by the same instructor. The estimates of column (1) are negative and statistically significant at the 5% level.[43] When I control for course request preferences

[41] I need to acknowledge that the way instructors curve students' final grades may affect my findings. Instructors may adjust final grades by each section or by course, and some departments may even adjust final grades for all sections even taught by different instructors. Hence, final course grades may provide a less precise measure of students' academic performance.

[42] In this study,

[43] For simplicity, I only interpret the 2SLS estimates. Estimates of 2SLS and reduced form are similar.

in column (2), the estimated results are now statistically significant at the 1% levels. After including students' demographic controls in column (3), the results indicate that students are less likely to enroll in the corresponding STEM courses by 5.9 percentage points (or 23%) within the next two terms at the 1% level.[44] Furthermore, I investigate the heterogeneous effects on the likelihood of taking corresponding STEM courses in Table 10. However, I do not see consistent heterogeneous effects on students' observable characteristics including gender, race, first generation status, and SAT scores.

6.2.2 The Propensity to Study a Corresponding Major

Table 11 discusses the propensity for students to study in a major directly corresponding to the assigned early morning classes. Similarly, I perform the 2SLS and the reduced form estimations of equations (1) and (2). I first regress an indicator for whether students study in a corresponding major by including the course-by-instructor fixed effect in column (1). I find that there are negative effects of attending early morning classes, but the estimates are imprecise in both columns (1). I further include course request preferences in column (2) and including demographic characteristics in column (3), early morning classes decrease the probability of choosing a corresponding major by 1.2 percentage points (or 68%) and 1.4 percentage points (or 76%). In Table 12, I further explore the heterogeneous effects of early morning classes on student's choice of major but find no evidence across students' demographic characteristics. In Figure 4, I illustrate the effects of different class times on major choice and find that the negative effect of early morning classes gradually fade away after 9:30 AM and show null effect later in the morning.[45]

In addition, I find that students who are assigned into early morning STEM classes are 1.6 percentage points (or 98%) less likely to study in a corresponding STEM major in column

[44] I also explore the likelihood of students taking additional corresponding STEM courses in the very next first term alone in Table A.10. Estimated results are robust.

[45] Since each estimation in Table 4 refers to different treatment groups, so readers should not make direct comparison with the same sample.

(2) of Table 13.[46] On the other hand, I find no evidence from being enrolled in early morning non-STEM classes.

In Table 14, I estimate the impact of early morning classes on whether students study in a major from the same college. I find that early morning classes reduces students' probability to choose a major from the corresponding college by 2.7 percentage points (or 26%).[47] Consistent with the approach of Table 13, I find that assignments to early morning STEM classes decrease the probability of studying in the major within the corresponding college by 3.4 percentage points (or 39%) in column (2) of Table 16.

6.2.3 The Likelihood of Graduating from a Lower-Earning Major

I further examine the effect of early morning classes on students' likelihood to graduate from a lower-earning major. The outcome variable of interest is an indicator of whether a student graduates from a lower-earning major. I define majors with lower earnings as major earning in the first quartile (Q1).

In column (1) of Table 17, I discovered that assignments to early morning classes increase the likelihood of graduating with a lower-earning major by 6.6 percentage points (or 26%). The central reason for graduating from a lower-earning major is enrollment in early morning STEM classes; in column (2) attendance in these classes results in an 8.1 percentage point (or 29.2%) increase in the likelihood of selecting a lower-earning major. Conversely, I found no indication that students graduating from lower-earning majors were influenced by enrollment in early morning non-STEM classes as shown in column (3). Results from columns (4) to (9) show no evidence that being assigned into early morning classes affects the probability to graduate from median-earning and higher-earning majors.

[46] This analysis includes students with a bachelor degree and students with their latest majors in their senior year.

[47] In Table 15, I do not find strong evidence of heterogeneous effects on major choice at college level.

6.2.4 Mechanisms of the Effects on Educational Decisions

I now discuss potential mechanisms of the negative effects on educational decisions. In addition to diminishing academic performance documented in Tables 4 and 5, there could be other mechanisms to my findings.

A potential mechanism is attribution bias.[48] In my context, this means that students may misattribute the negative effect of early morning classes to their overall interest in a subject. Results from my students' survey show attribution bias as a piece of suggestive evidence. From columns (5) to (6) of Panel 2 in Table 6, I find that students enjoy attending fewer classes. However, it is unclear if students desire to take another corresponding course in the future.

7 Discussion and Conclusion

This paper analyzes the effect of early morning classes on students' human capital accumulation and academic trajectories: the likelihood of taking corresponding STEM courses and the propensity to study a corresponding major. Through a random class assignment algorithm, I document the causal effects that students receive lower academic performance, are less likely to take corresponding STEM courses in future terms, become less likely to study in a corresponding major, and increase the probability to graduate from a lower-learning major.

This study provides more representative findings and has a higher relevance to future labor market outcomes than prior studies by using a new administrative dataset at a large public university in the U.S. The institutional setting of Purdue University is more consistent with the settings of other public universities than the military and educational institutions like the USMA and USAFA (Carrell *et al.*, 2011; Williams & Shapiro, 2018; Haggag *et al.*, 2021). I also provide field survey evidence to support my empirical findings.

[48]Haggag *et al.* (2019) and (Haggag *et al.*, 2021) also discuss attribution bias.

From the field survey, I find that students become less motivated and participate less in early morning class. However, the result is not driven by instructor's teaching quality documented from both empirical and survey results. In my survey data, I find suggestive evidence of attribution bias, which is consistent with the findings of Haggag *et al.* (2021).

As policymakers strive to encourage students, they may want to make adjustments to university course schedules. Universities may schedule more introductory STEM courses (i.e., Chemistry 1 and Calculus 1) later in the morning and more humanity and other non-STEM courses in the early morning. Universities should consider having later class start times. University students at the age of 18 and 19 are still experiencing the changes of their circadian rhythm. It therefore becomes difficult for them to stay attentive during early morning classes (Crowley *et al.*, 2007; Pandi-Perumal *et al.*, 2008; Carrell *et al.*, 2011).

8 Figures and Tables

Figure 1: Course Registration Timeline

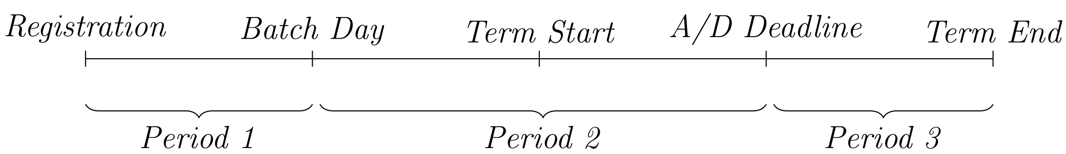
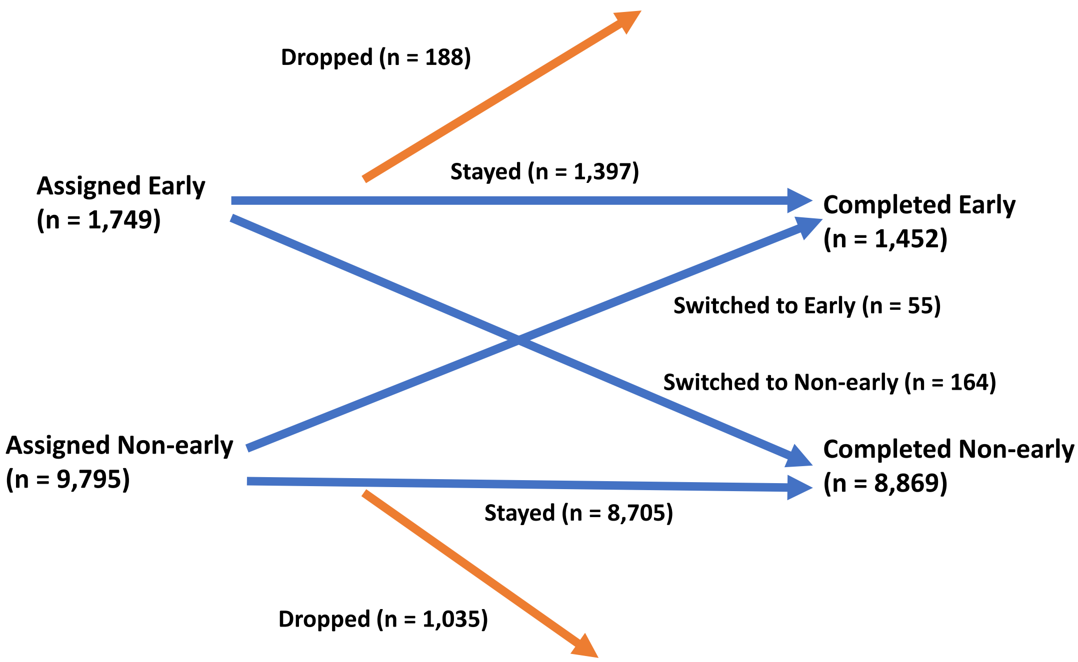


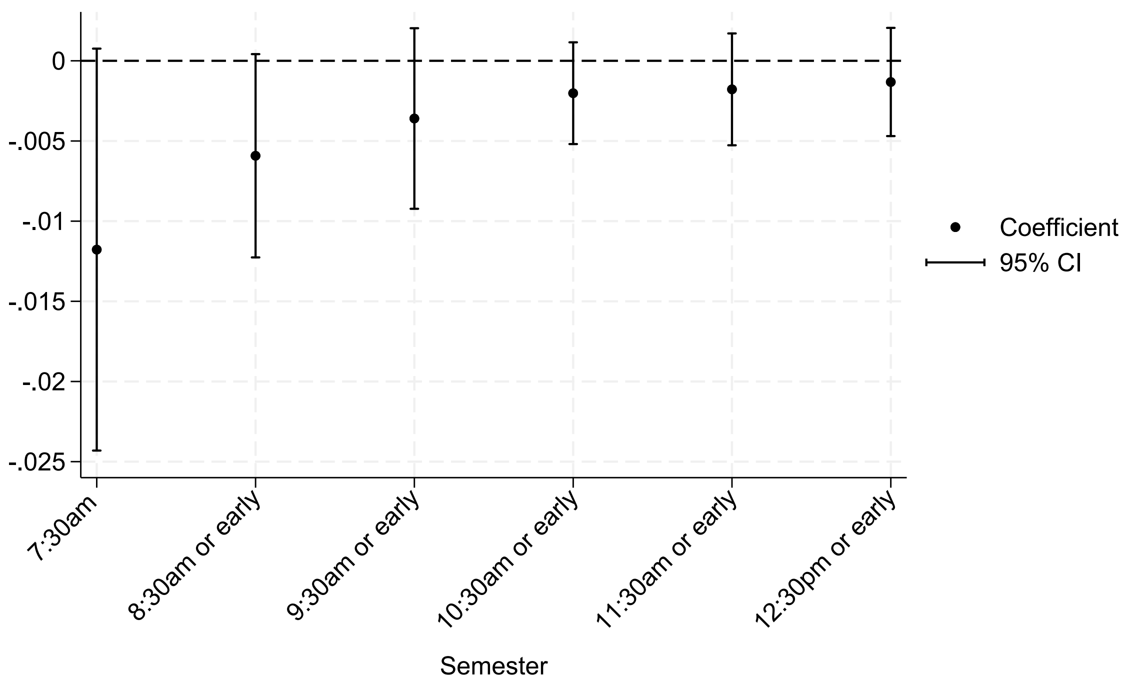
Figure 2: Class Compliance Comparisons in Econ 25200

Figure 3: Selection Diagram



Notes: The observations are in course-by-student-by-term level from the Grade sample.

Figure 4: Effects of Different Class Times on Major Choice



Notes: Each estimation refers to different sets of sample since there are students from courses that may be in the control group at 7:30 AM specification but may be in the treatment group at 8:30 am specification.

Table 1: Summary Statistics

	Grade Sample		STEM Sample		Major Sample	
	Assigned Early	Assigned Non-Early	Assigned Early	Assigned Non-Early	Assigned Early	Assigned Non-Early
Female	0.639	0.546	0.653	0.562	0.619	0.524
	(0.480)	(0.498)	(0.476)	(0.496)	(0.486)	(0.499)
White	0.763	0.724	0.769	0.740	0.755	0.704
	(0.425)	(0.447)	(0.422)	(0.439)	(0.430)	(0.456)
Black	0.0417	0.0477	0.0468	0.0489	0.0356	0.0460
	(0.200)	(0.213)	(0.211)	(0.216)	(0.185)	(0.209)
Hispanic	0.0585	0.0612	0.0578	0.0618	0.0593	0.0603
	(0.235)	(0.240)	(0.233)	(0.241)	(0.236)	(0.2380)
Asian	0.115	0.147	0.106	0.129	0.128	0.170
	(0.319)	(0.354)	(0.307)	(0.335)	(0.334)	(0.376)
Other	0.0211	0.0201	0.0211	0.0211	0.0211	0.0187
	(0.144)	(0.140)	(0.144)	(0.144)	(0.144)	(0.136)
1st Gen Student	0.174	0.186	0.187	0.198	0.155	0.170
	(0.380)	(0.389)	(0.390)	(0.399)	(0.363)	(0.376)
SAT Combined	1238.911	1251.904	1235.11	1243.915	1243.518	1261.992
	(120.613)	(122.92)	(118.959)	(116.189)	(123.432)	(130.600)
Requested Course	13.428	13.0381	13.289	12.936	13.169	13.174
	(3.504)	(3.474)	(3.496)	(3.569)	(3.508)	(3.342)
N	1,846	7,174	1,090	4,028	759	3,153

Notes: The observations are in student-by-course-by-term level. The middle panel displays observations of domestic freshman students from Fall 2018, Fall 2019, and Spring 2020 in my STEM-course analyses. I call those observations as "STEM Sample". The right panel displays observations of domestic freshman students from Fall 2018 in my choice-of-a-major analyses. I call those observations as "Major Sample". The observations of "Grade Sample" is 9,020, which is lower the number of total observations (9,030) combined with "STEM" and "Major" samples because there are 10 course-student observations that do not report a letter grade. Standard deviation is in parentheses.

Table 2: Student-by-Course-by-Term Level Balance Test

	(1)	(2)	(3)
Female	0.049**	0.005	0.005
	(0.019)	(0.008)	(0.008)
Black	-0.018	-0.004	-0.006
	(0.022)	(0.017)	(0.017)
Hispanic	-0.008	-0.005	-0.003
	(0.013)	(0.007)	(0.007)
Asian	-0.023*	-0.011	-0.011
	(0.013)	(0.009)	(0.010)
Other Race/Ethnicity	-0.020	-0.008	-0.006
	(0.026)	(0.025)	(0.025)
First Generation	-0.012	-0.010	-0.009
	(0.013)	(0.009)	(0.009)
Standardized SAT Combined	-0.015*	-0.005	-0.005
	(0.009)	(0.004)	(0.004)
F-stat P-Value	0.129	0.134	0.23
Observations	9,626	9,626	9,626
R^2	0.008	0.376	0.377
Course-Instructor-Term FE	N	Y	Y
Course Preference Controls	N	Y	Y
Number of Courses Requested FE	N	N	Y

Notes: Robust standard errors in parentheses are clustered at the individual and course-by-term levels (6,595 clusters at the individual level and 197 clusters for course-by-instructor-by-term level). The outcome in this regression is an indicator for whether students were assigned to an early morning class. SAT combined is a standardized variable with mean of zero and standard deviation of one. Observations are domestic non-athlete freshman cohort between the age of 18 and 21 from Fall 2018, Fall 2019, and Spring 2020. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: First Stage Estimates

	Panel 1: STEM Sample		
	(1)	(2)	(3)
Assigned 7:30 AM Section	0.853***	0.851***	0.851***
	(0.0271)	(0.0276)	(0.0277)
Course-Instructor-Term FE	Y	Y	Y
Course Request Controls	N	Y	Y
Demographic Controls	N	N	Y
F-Statistics	995.271	947.936	948.967
N	5,118	5,118	5,118
R^2	0.861	0.861	0.862
	Panel 2: Major Sample		
	(1)	(2)	(3)
Assigned 7:30 AM Section	0.870***	0.864***	0.864***
	(0.0300)	(0.0310)	(0.0280)
Course-Instructor FE	Y	Y	Y
Course Request Controls	N	Y	Y
Demographic Controls	N	N	Y
F-Statistics	838.096	779.575	782.017
N	3,963	3,963	3,963
R^2	0.901	0.901	0.902

Notes: Panel 1 shows the first stage estimates. The observations of Panel 1 are domestic non-athlete freshman cohort between the age of 18 and 21 from Fall 2018, Fall 2019, and Spring 2020 who registered to lower-level (100 or 200 level) STEM classes either in an early morning (7:30 AM) section or a non-early morning section. These observations are included into my STEM-course analyses. There are 61 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. Robust standard errors in parentheses are clustered at the individual and section-by-term levels (4,088 clusters at the individual level and 166 clusters for section-by-term level). Similarly, Panel 2 shows the first stage estimates. The observations are domestic freshman cohort between the age of 18 and 21 from Fall 2018 who registered to lower-level (100 or 200 level) either in an early morning (7:30 AM) class or a non-early morning class. These observations are included into my choice-of-a-major analyses. There are 40 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. Robust standard errors in parentheses are clustered at the individual and section-by-term levels (2,844 clusters at the individual level and 237 clusters for section-by-term level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effect on Course Grades

	Panel 1: 2SLS Estimates		
	(1)	(2)	(3)
Assigned 7:30 AM Section	-0.0806	-0.0559	-0.0598**
	(0.0518)	(0.0420)	(0.0276)
Course-Instructor-Term FE	Y	Y	Y
Course Request Controls	N	Y	Y
Demographic Controls	N	N	Y
N	9,020	9,020	9,020
Dependent Variable Mean	3.00	3.00	3.00
	Panel 2: Reduced Form Estimates		
	(1)	(2)	(3)
Assigned 7:30 AM Section	-0.0687	-0.0475	-0.0509**
	(0.0438)	(0.0353)	(0.0230)
Course-Instructor-Term FE	Y	Y	Y
Course Request Controls	N	Y	Y
Demographic Controls	N	N	Y
N	9,020	9,020	9,020
R^2	0.119	0.130	0.240
Dependent Variable Mean	3.00	3.00	3.00

Notes: Observations are domestic non-athlete freshman students between the age of 18 and 21 from Fall 2018, Fall 2019, and Spring 2020. There are 78 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. Robust standard errors in parentheses are clustered at the individual and course-by-term levels (5,029 clusters at the individual level and 311 clusters for section-by-term level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effect on Getting Different Grades

	Letter Grades or Above										
	A or above (1)	A- or above (2)	B+ or above (3)	B or above (4)	B- or above (5)	C+ or above (6)	C or above (7)	C- or above (8)	D+ or above (9)	D or above (10)	D- or above (11)
Assigned 7:30 AM Section	-0.0110	-0.0176	-0.0205*	-0.0306***	-0.0295***	-0.0219*	-0.00409	-0.00912	-0.00342	-0.00280	-0.00507
	(0.0118)	(0.0129)	(0.0112)	(0.0107)	(0.0105)	(0.0112)	(0.00854)	(0.00805)	(0.00669)	(0.00647)	(0.00621)
Course-Instructor-Term FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Course Request Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	9,020	9,020	9,020	9,020	9,020	9,020	9,020	9,020	9,020	9,020	9,020
R^2	0.191	0.199	0.217	0.190	0.174	0.169	0.105	0.097	0.094	0.094	0.049
Dependent Variable Mean	0.306	0.384	0.464	0.680	0.723	0.783	0.888	0.913	0.931	0.965	0.971

Notes: Observations are domestic non-athlete freshman students between the age of 18 and 21 from Fall 2018, Fall 2019, and Spring 2020. There are 78 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. Robust standard errors in parentheses are clustered at the individual and course-by-term levels (5,029 clusters at the individual level and 311 clusters for section-by-term level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Effect of Assigned Early Morning Classes on Students' Class Experiences

	Panel 1				
	Class Participation (1)	Classmate Participation (2)	Increase Critical Thinking (3)	Class Motivate Learning (4)	Learn More in Diff. Section (5)
Assigned 7:30 AM Section	-0.124**	-0.00835	-0.0220	-0.0966*	0.247***
	(0.0518)	(0.0635)	(0.0622)	(0.0560)	(0.0548)
Student School Year FE	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y
N	343	343	343	343	343
R^2	0.115	0.067	0.035	0.082	0.218
Dependent Variable Mean	0.233	0.455	0.627	0.758	0.271

	Panel 2					
	Clear Lecture (1)	Engaging Lecture (2)	Instructor Help Learning (3)	Instructor Enthusiastic (4)	Enjoy Attending Classes (5)	Desire Another Econ Course (6)
Assigned 7:30 AM Section	-0.0178	-0.0531	-0.00482	-0.0404	-0.104*	0.0418
	(0.0335)	(0.0541)	(0.0478)	(0.0403)	(0.0595)	(0.0596)
Student School Year FE	Y	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y	Y
N	343	343	343	343	343	343
R^2	0.026	0.037	0.053	0.078	0.078	0.172
Dependent Variable Mean	0.936	0.773	0.857	0.904	0.674	0.516

Notes: Observations are students from ECON 25200 course in Fall 2022. There are two sections (7:30 AM and 9:30 AM) taught by the same instructor. The dependent variables are indicators for whether students answer "Strongly Agree" and "Agree." Columns (1), (2), (3), (4), and (5) of Panel 1 are outcomes related to student's learning; columns (1), (2), (3), and (4) of Panel 2 are outcomes related to the course instructor, and columns (5) and (6) of Panel 2 are outcomes related to student's interest on the course subject. ECON 25200 is an introductory macroeconomics course offered by the Krannert School of Management at Purdue University. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Effect of Attending Subsequent Classes on Course Grades

	Course GPA (1)	B or above (2)	Letter Grade As (3)	Letter Grade Cs (4)
Subsequent Section	0.00444	0.00134	0.00158	0.00254
	(0.0385)	(0.0183)	(0.0208)	(0.0108)
Course-Instructor-Term FE	Y	Y	Y	Y
Course-Time FE	Y	Y	Y	Y
Course Request Controls	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y
N	34,783	34,783	34,783	34,783
R^2	0.272	0.213	0.309	0.110
Dependent Variable Mean	3.21	0.770	0.506	0.0823

Notes: Observations are from domestic non-athlete freshman cohort from Fall 2018, Fall 2019, and Spring 2020. Observations are higher than my regression sample in my previous results because in this regression, I estimate the effect of attending subsequent classes on all undergraduate-level courses with multiple sections taught by the same instructors from Fall 2018, Fall 2019, and Spring 2020. It means that courses with multiple sections offered in the non-early morning period, late in the morning or in the afternoon would be included in this analysis. Robust standard errors in parentheses are clustered at the individual and section-by-term levels (9,664 clusters at the individual level and 1701 clusters for section-by-term level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Effect on Leave-One-Out Term GPA

	Panel 1: 2SLS Estimates		
	(1)	(2)	(3)
Assigned 7:30 AM Section	0.0135	0.0276	0.0214
	(0.0388)	(0.0337)	(0.0294)
Course-Instructor-Term FE	Y	Y	Y
Course Request Controls	N	Y	Y
Demographic Controls	N	N	Y
N	8,981	8,981	8,981
Dependent Variable Mean	3.21	3.21	3.21
	Panel 2: Reduced Form Estimates		
	(1)	(2)	(3)
Assigned 7:30 AM Section	0.0115	0.0235	0.0191
	(0.0331)	(0.0286)	(0.0250)
Course-Instructor-Term FE	Y	Y	Y
Course Request Controls	N	Y	Y
Demographic Controls	N	N	Y
N	8,981	8,981	8,981
R^2	0.057	0.072	0.147
Dependent Variable Mean	3.21	3.21	3.21

Notes: Observations are domestic non-athlete freshman students between the age of 18 and 21 from Fall 2018, Fall 2019, and Spring 2020. The number of observation is 8,981 that is lower than the number of observation (9,020) in Table 5 because 39 students only took one course. There are 78 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. Robust standard errors in parentheses are clustered at the individual and course-by-term levels (5,029 clusters at the individual level and 311 clusters for section-by-term level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Effect on STEM Courses within the Next 2 Terms

	Panel 1: 2SLS Estimates		
	(1)	(2)	(3)
Assigned 7:30 AM Section	-0.0485**	-0.0577***	-0.0592***
	(0.0219)	(0.0204)	(0.0201)
Course-Instructor-Term FE	Y	Y	Y
Course Request Controls	N	Y	Y
Demographic Controls	N	N	Y
N	5,118	5,118	5,118
Dependent Variable Mean	0.260	0.260	0.260
	Panel 2: Reduced Form Estimates		
	(1)	(2)	(3)
Assigned 7:30 AM Section	-0.0414**	-0.0491***	-0.0535***
	(0.0190)	(0.0179)	(0.0172)
Course-Instructor-Term FE	Y	Y	Y
Course Request Controls	N	Y	Y
Demographic Controls	N	N	Y
N	5,118	5,118	5,118
R^2	0.070	0.093	0.089
Dependent Variable Mean	0.260	0.260	0.260

Notes: Observations are domestic non-athlete freshman cohort between the age of 18 and 21 from Fall 2018, Fall 2019, and Spring 2020. There are 61 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. Robust standard errors in parentheses are clustered at the individual and section-by-term levels (4,088 clusters at the individual level and 166 clusters for section-by-term level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Heterogeneous Effect on Taking Corresponding STEM Courses within the Next Two Term

	(1)	(2)	(3)	(4)	(5)
Assigned 7:30 AM Section	-0.0535***	-0.0201	-0.0556***	-0.0565***	-0.0552***
	(0.0172)	(0.0353)	(0.0167)	(0.0167)	(0.0161)
Female × Assigned 7:30 AM Section		-0.0483			
		(0.0372)			
Black × Assigned 7:30 AM Section			0.0421		
			(0.0669)		
Hispanic × Assigned 7:30 AM Section			-0.0380		
			(0.0488)		
Asian × Assigned 7:30 AM Section			-0.0265		
			(0.0565)		
Other × Assigned 7:30 AM Section			0.0982		
			(0.145)		
Standardized SAT × Assigned 7:30 AM Section				-0.0141	
				(0.0213)	
1st Gen Student × Assigned 7:30 AM Section					0.00813
					(0.0480)
Course-Instructor-Term-term FE	Y	Y	Y	Y	Y
Course Request Controls	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y
N	5,118	5,118	5,118	5,118	5,118
R^2	0.089	0.090	0.090	0.090	0.089
Dependent Variable Mean	0.260	0.260	0.260	0.260	0.260

Notes: Observations are domestic non-athlete freshman cohort between the age of 18 and 21 from Fall 2018, Fall 2019, and Spring 2020. There are 61 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. Robust standard errors in parentheses are clustered at the individual and course-by-term levels (4,088 clusters at the individual level and 166 clusters for section-by-term level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Effect on Choice of Major

	Panel 1: 2SLS Estimates		
	(1)	(2)	(3)
Assigned 7:30 AM Section	-0.0110	-0.0123*	-0.0141*
	(0.00757)	(0.00739)	(0.00746)
Course-Instructor FE	Y	Y	Y
Course Request Controls	N	Y	Y
Demographic Controls	N	N	Y
N	3,912	3,912	3,912
Dependent Variable Mean	0.0179	0.0179	0.0179
	Panel 2: Reduced Form Estimates		
	(1)	(2)	(3)
Assigned 7:30 AM Section	-0.00973	-0.0109*	-0.0124*
	(0.00669)	(0.00652)	(0.00656)
Course-Instructor FE	Y	Y	Y
Course Request Controls	N	Y	Y
Demographic Controls	N	N	Y
N	3,912	3,912	3,912
R^2	0.281	0.287	0.292
Dependent Variable Mean	0.0179	0.0179	0.0179

Notes: Observations are domestic non-athlete freshman cohort between the age of 18 and 21 from Fall 2018. There are 40 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. Robust standard errors in parentheses are clustered at the individual and section levels (2,812 clusters at the individual level and 237 clusters for section level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Heterogeneous Effect on Choice of Major

	(1)	(2)	(3)	(4)	(5)
Assigned 7:30 AM Section	-0.0124*	-0.0213	-0.0130**	-0.0104	-0.00842
	(0.00656)	(0.0142)	(0.00609)	(0.00641)	(0.00674)
Female × Assigned 7:30 AM Section		0.0140			
		(0.0177)			
Black × Assigned 7:30 AM Section			0.0305*		
			(0.0165)		
Hispanic × Assigned 7:30 AM Section			-0.0240		
			(0.0327)		
Asian × Assigned 7:30 AM Section			0.0107		
			(0.0117)		
Other × Assigned 7:30 AM Section			-0.0148		
			(0.0168)		
Standardized SAT × Assigned 7:30 AM Section				0.00641	
				(0.00500)	
1st Gen Student × Assigned 7:30 AM Section					-0.0202
					(0.0165)
Course-Instructor FE	Y	Y	Y	Y	Y
Course Request Controls	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y
N	3,912	3,912	3,912	3,912	3,912
R^2	0.291	0.311	0.311	0.303	0.303
Dependent Variable Mean	0.0179	0.0179	0.0179	0.0179	0.292

Notes: Observations are domestic non-athlete freshman cohort between the age of 18 and 21 from Fall 2018. There are 40 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. In column (4), I use white students as the reference group, and Other refers to Native American students and students with non-disclosure ethnicity. Robust standard errors in parentheses are clustered at the individual and course-by-term levels (2,812 clusters at the individual level and 237 clusters for section-by-term level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Effect on Choice of STEM Major

	Overall	STEM	Non-STEM
	(1)	(2)	(3)
Assigned 7:30 AM Section	-0.0124*	-0.0161**	0.0370
	(0.00656)	(0.00639)	(0.0445)
Course-Instructor FE	Y	Y	Y
Course Request Controls	Y	Y	Y
Demographic Controls	Y	Y	Y
N	3,912	2,555	1,357
R^2	0.292	0.448	0.095
Dependent Variable Mean	0.0177	0.0164	0.0209

Notes: Observations are domestic non-athlete freshman cohort between the age of 18 and 21 from Fall 2018. There are 40 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. Robust standard errors in parentheses are clustered at the individual and section levels (2,812, 1,995, and 1,293 clusters at the individual level and 237, 90, and 147 clusters for section level in columns 1, 2, and 3 respectively). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Effect on Choice of Major (College Level)

	Panel 1: 2SLS Estimates		
	(1)	(2)	(3)
Assigned 7:30 AM Section	-0.0234*	-0.0239*	-0.0270*
	(0.0129)	(0.0141)	(0.0142)
Course-Instructor FE	Y	Y	Y
Course Request Controls	N	Y	Y
Demographic Controls	N	N	Y
N	3,912	3,912	3,912
Dependent Variable Mean	0.104	0.104	0.104
	Panel 2: Reduced Form Estimates		
	(1)	(2)	(3)
Assigned 7:30 AM Section	-0.0207*	-0.0210*	-0.0216*
	(0.0112)	(0.0122)	(0.0123)
Course-Instructor FE	Y	Y	Y
Course Request Controls	N	Y	Y
Demographic Controls	N	N	Y
N	3,912	3,912	3,912
R^2	0.198	0.209	0.225
Dependent Variable Mean	0.104	0.104	0.104

Notes: Observations are domestic non-athlete freshman cohort between the age of 18 and 21 from Fall 2018. There are 40 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. Robust standard errors in parentheses are clustered at the individual and section levels (2,844 clusters at the individual level and 237 clusters for section level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Heterogeneous Effect on Choice of Major (Department Level)

	(1)	(2)	(3)	(4)	(5)
Assigned 7:30 AM Section	-0.0216*	-0.0500	-0.0214	-0.0234*	-0.0154
	(0.0123)	(0.0389)	(0.0132)	(0.0137)	(0.0135)
Female × Assigned 7:30 AM Section		0.0445			
		(0.0512)			
Black × Assigned 7:30 AM Section			-0.0386		
			(0.0370)		
Hispanic × Assigned 7:30 AM Section			-0.0435		
			(0.0654)		
Asian × Assigned 7:30 AM Section			0.0148		
			(0.0373)		
Other × Assigned 7:30 AM Section			0.0660		
			(0.0829)		
Standardized SAT × Assigned 7:30 AM Section				-0.00853	
				(0.0206)	
1st Gen Student × Assigned 7:30 AM Section					-0.0377
					(0.0288)
Course-Instructor FE	Y	Y	Y	Y	Y
Course Request Controls	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y
N	3,912	3,912	3,912	3,912	3,912
R^2	0.225	0.225	0.225	0.225	0.225
Dependent Variable Mean	0.104	0.104	0.104	0.104	0.104

Notes: Observations are domestic non-athlete freshman cohort between the age of 18 and 21 from Fall 2018. There are 40 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. In column (4), I use white students as the reference group, and Other refers to Native American students and students with non-disclosure ethnicity. Robust standard errors in parentheses are clustered at the individual and course-by-term levels (2,844 clusters at the individual level and 237 clusters for section-by-term level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Effect on Choice of STEM Major (College Level)

	Overall	STEM	Non-STEM
	(1)	(2)	(3)
Assigned 7:30 AM Section	-0.0216*	-0.0343***	0.0537
	(0.0123)	(0.0111)	(0.0874)
Course-Instructor FE	Y	Y	Y
Course Request Controls	Y	Y	Y
Demographic Controls	Y	Y	Y
N	3,912	2,555	1,357
R^2	0.225	0.260	0.234
Dependent Variable Mean	0.104	0.0881	0.135

Notes: Observations are domestic non-athlete freshman cohort between the age of 18 and 21 from Fall 2018. There are 40 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. Robust standard errors in parentheses are clustered at the individual and section levels (2,812, 1,995, and 1,293 clusters at the individual level and 237, 90, and 147 clusters for section level in columns 1, 2, and 3 respectively). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Effect on Major Earnings

	Q1			Q2			Q3		
	Combined (1)	STEM (2)	Non-STEM (3)	Combined (4)	STEM (5)	Non-STEM (6)	Combined (7)	STEM (8)	Non-STEM (9)
Assigned 7:30 AM Section	0.0655***	0.0805***	-0.0127	0.0138	0.0168	0.0520	0.00910	0.0133	0.0458
	(0.0204)	(0.0208)	(0.0765)	(0.0283)	(0.0325)	(0.0682)	(0.0168)	(0.0138)	(0.0440)
Course-Instructor-Term FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Course Request Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	3,911	2,555	1,357	3,911	2,555	1,357	3,911	2,555	1,357
R^2	0.145	0.119	0.228	0.286	0.239	0.373	0.318	0.230	0.447
Dependent Variable Mean	0.252	0.276	0.206	0.500	0.551	0.405	0.743	0.807	0.620

Notes: Observations are domestic non-athlete freshman cohort between the age of 18 and 21 from Fall 2018. There are 40 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. Q1 refers to the college-major earnings that fall into the 25th percentile major-earning distribution. In columns (1), (2), and (3), the outcome variable is an indicator for whether students graduated from a college major that is under the 1st quartile major earnings. Q2 refers to the college-major earnings that fall into the 50th percentile major-earning distribution. In columns (4), (5), and (6), the outcome variable is an indicator for whether students graduated from a college major that is under the 2nd quartile major earnings. Q3 refers to the college-major earnings that fall into the 75th percentile major-earning distribution. In columns (7), (8), and (9), the outcome variable is an indicator for whether students graduated from a college major that is under the 3rd quartile major earnings. Robust standard errors in parentheses are clustered at the individual and section levels (2,812 at the individual level in columns (1), (4) & (7) respectively, 1,995 at the individual level in columns (2), (5) & (8) respectively, and 1,293 clusters at the individual level in column (3), (6), & (9) and 237 clusters for section level in columns (1), (4) & (7) respectively, 90 clusters for section level in columns (2), (5) & (8) respectively, and 147 clusters for section level in columns (3), (6), & (9) respectively). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

References

Altonji, Joseph G, Blom, Erica, & Meghir, Costas. 2012. Heterogeneity in human capital investments: High school curriculum, college major, and careers. *Annu. Rev. Econ.*, **4**(1), 185–223.

Altonji, Joseph G, Kahn, Lisa B, & Speer, Jamin D. 2014. Trends in earnings differentials across college majors and the changing task composition of jobs. *American Economic Review*, **104**(5), 387–393.

Andrews, Rodney J, Imberman, Scott A, & Lovenheim, Michael F. 2017. *Risky business? The effect of majoring in business on earnings and educational attainment*. Tech. rept. National Bureau of Economic Research.

Arcidiacono, Peter. 2004. Ability sorting and the returns to college major. *Journal of Econometrics*, **121**(1-2), 343–375.

Barnes, Christopher M, & Wagner, David T. 2009. Changing to daylight saving time cuts into sleep and increases workplace injuries. *Journal of applied psychology*, **94**(5), 1305.

Bleemer, Zachary, & Mehta, Aashish. 2021. College major restrictions and student stratification. *Available at SSRN 3981921*.

Bleemer, Zachary, & Mehta, Aashish. 2022. Will studying economics make you rich? A regression discontinuity analysis of the returns to college major. *American Economic Journal: Applied Economics*, **14**(2), 1–22.

Canes-Wrone, Brandice, & Rosen, Harvey S. 1994. *Following in her footsteps? Women's choices of college majors and faculty gender composition*.

Cardinali, Daniel P. 2008. Chronoeducation: How the biological clock influences the learning process. *The educated brain: Essays in neuroeducation*, 110–26.

Carrell, Scott E, Fullerton, Richard L, & West, James E. 2009. Does your cohort matter? Measuring peer effects in college achievement. *Journal of Labor Economics*, **27**(3), 439–464.

Carrell, Scott E, Maghakian, Teny, & West, James E. 2011. A's from Zzzz's? The causal effect of school start time on the academic achievement of adolescents. *American Economic Journal: Economic Policy*, **3**(3), 62–81.

Carskadon, Mary A, Vieira, Cecilia, & Acebo, Christine. 1993. Association between puberty and delayed phase preference. *Sleep*, **16**(3), 258–262.

Chevalier, Arnaud. 2011. Subject choice and earnings of UK graduates. *Economics of Education Review*, **30**(6), 1187–1201.

Cosgrave, Jan, Wulff, Katharina, & Gehrman, Philip. 2018. Sleep, circadian rhythms, and schizophrenia: where we are and where we need to go. *Current opinion in psychiatry*, **31**(3), 176–182.

Crowley, Stephanie J, Acebo, Christine, & Carskadon, Mary A. 2007. Sleep, circadian rhythms, and delayed phase in adolescence. *Sleep medicine*, **8**(6), 602–612.

Dee, Thomas S. 2004. Teachers, race, and student achievement in a randomized experiment. *Review of economics and statistics*, **86**(1), 195–210.

Dee, Thomas S. 2005. A teacher like me: Does race, ethnicity, or gender matter? *American Economic Review*, **95**(2), 158–165.

Denning, Jeffrey T, & Turley, Patrick. 2017. Was that SMART? Institutional financial incentives and field of study. *Journal of Human Resources*, **52**(1), 152–186.

Diette, Timothy M, & Raghav, Manu. 2017. Does early bird catch the worm or a lower GPA? Evidence from a liberal arts college. *Applied Economics*, **49**(33), 3341–3350.

Dills, Angela K, & Hernandez-Julian, Rey. 2008. Course scheduling and academic performance. *Economics of Education Review*, **27**(6), 646–654.

Edwards, Finley. 2012. Early to rise? The effect of daily start times on academic performance. *Economics of Education Review*, **31**(6), 970–983.

Ehrenberg, Ronald G, & Brewer, Dominic J. 1995. Did teachers' verbal ability and race matter in the 1960s? Coleman revisited. *Economics of Education Review*, **14**(1), 1–21.

Ehrenberg, Ronald G, Goldhaber, Daniel D, & Brewer, Dominic J. 1995. Do teachers' race, gender, and ethnicity matter? Evidence from the National Educational Longitudinal

Study of 1988. *ILR Review*, **48**(3), 547–561.

García, Aída, Ramírez, Candelaria, Martínez, Benito, & Valdez, Pablo. 2012. Circadian rhythms in two components of executive functions: cognitive inhibition and flexibility. *Biological Rhythm Research*, **43**(1), 49–63.

Goldstein, David, Hahn, Constanze S, Hasher, Lynn, Wiprzycka, Ursula J, & Zelazo, Philip David. 2007. Time of day, intellectual performance, and behavioral problems in morning versus evening type adolescents: Is there a synchrony effect? *Personality and individual Differences*, **42**(3), 431–440.

Groen, Jeffrey A, & Pabilonia, Sabrina Wulff. 2019. Snooze or lose: High school start times and academic achievement. *Economics of Education Review*, **72**, 204–218.

Haggag, Kareem, Pope, Devin G, Bryant-Lees, Kinsey B, & Bos, Maarten W. 2019. Attribution bias in consumer choice. *The Review of Economic Studies*, **86**(5), 2136–2183.

Haggag, Kareem, Patterson, Richard W, Pope, Nolan G, & Feudo, Aaron. 2021. Attribution bias in major decisions: Evidence from the United States Military Academy. *Journal of Public Economics*, **200**, 104445.

Hasler, Brant P, Soehner, Adriane M, & Clark, Duncan B. 2014. Circadian rhythms and risk for substance use disorders in adolescence. *Current opinion in psychiatry*, **27**(6), 460.

Hastings, Justine S, Neilson, Christopher A, & Zimmerman, Seth D. 2013. *Are some degrees worth more than others? Evidence from college admission cutoffs in Chile*. Tech. rept. National Bureau of Economic Research.

Hoffmann, Florian, & Oreopoulos, Philip. 2009. A professor like me the influence of instructor gender on college achievement. *Journal of human resources*, **44**(2), 479–494.

Horne, Jim, & Reyner, Louise. 1999. Vehicle accidents related to sleep: a review. *Occupational and environmental medicine*, **56**(5), 289–294.

Jagnani, Maulik. 2018. Poor sleep: Sunset time and human capital production. *Mimeo*.

Kecklund, Göran, & Axelsson, John. 2016. Health consequences of shift work and insufficient sleep. *Bmj*, **355**.

Kirkeboen, Lars J, Leuven, Edwin, & Mogstad, Magne. 2016. Field of study, earnings, and self-selection. *The Quarterly Journal of Economics*, **131**(3), 1057–1111.

Klopfenstein, Kristin. 2005. Beyond test scores: The impact of Black teacher role models on rigorous math taking. *Contemporary Economic Policy*, **23**(3), 416–428.

Müller, Tomáš, & Murray, Keith. 2010. Comprehensive approach to student sectioning. *Annals of Operations Research*, **181**(1), 249–269.

Nakata, Akinori, Ikeda, Tomoko, Takahashi, Masaya, Haratani, Takashi, Fujioka, Yosei, Fukui, Satoe, Swanson, Naomi G, Hojou, Minoru, & Araki, Shunichi. 2005. Sleep-related risk of occupational injuries in Japanese small and medium-scale enterprises. *Industrial health*, **43**(1), 89–97.

Pandi-Perumal, Seithikurippu R, Trakht, Ilya, Srinivasan, Venkataramanujan, Spence, D Warren, Maestroni, Georges JM, Zisapel, Nava, & Cardinali, Daniel P. 2008. Physiological effects of melatonin: role of melatonin receptors and signal transduction pathways. *Progress in neurobiology*, **85**(3), 335–353.

Patnaik, Arpita, Venator, Joanna, Wiswall, Matthew, & Zafar, Basit. 2020. *The Role of Heterogeneous Risk Preferences, Discount Rates, and Earnings Expectations in College Major Choice.* Tech. rept. National Bureau of Economic Research.

Persson, Jonas, Welsh, Kathryn M, Jonides, John, & Reuter-Lorenz, Patricia A. 2007. Cognitive fatigue of executive processes: Interaction between interference resolution tasks. *Neuropsychologia*, **45**(7), 1571–1579.

Pope, Nolan G. 2016. How the time of day affects productivity: Evidence from school schedules. *Review of Economics and Statistics*, **98**(1), 1–11.

Price, Joshua. 2010. The effect of instructor race and gender on student persistence in STEM fields. *Economics of Education Review*, **29**(6), 901–910.

Rask, Kevin N, & Bailey, Elizabeth M. 2002. Are faculty role models? Evidence from major choice in an undergraduate institution. *The Journal of Economic Education*, **33**(2), 99–124.

Robb, Roberta Edgecombe, & Robb, A Leslie. 1999. Gender and the study of economics: The role of gender of the instructor. *The Journal of Economic Education*, **30**(1), 3–19.

Robst, John, Keil, Jack, & Russo, Dean. 1998. The effect of gender composition of faculty on student retention. *Economics of Education Review*, **17**(4), 429–439.

Schmidt, Christina, Collette, Fabienne, Cajochen, Christian, & Peigneux, Philippe. 2007. A time to think: circadian rhythms in human cognition. *Cognitive neuropsychology*, **24**(7), 755–789.

Sjoquist, David L, & Winters, John V. 2015. State merit aid programs and college major: A focus on STEM. *Journal of Labor Economics*, **33**(4), 973–1006.

Van Den Berg, Johannes, & Neely, Gregory. 2006. Performance on a simple reaction time task while sleep deprived. *Perceptual and Motor Skills*, **102**(2), 589–599.

Webber, Douglas A. 2014a. The lifetime earnings premia of different majors: Correcting for selection based on cognitive, noncognitive, and unobserved factors. *Labour economics*, **28**, 14–23.

Webber, Douglas A. 2014b. The lifetime earnings premia of different majors: Correcting for selection based on cognitive, noncognitive, and unobserved factors. *Labour economics*, **28**, 14–23.

Williams, Kevin M, & Shapiro, Teny Maghakian. 2018. Academic achievement across the day: Evidence from randomized class schedules. *Economics of Education Review*, **67**, 158–170.

Wolfson, Amy R, & Carskadon, Mary A. 1998. Sleep schedules and daytime functioning in adolescents. *Child development*, **69**(4), 875–887.

Wolfson, Amy R, & Carskadon, Mary A. 2005. A survey of factors influencing high school starttimes. *NASSP Bulletin*, **89**(642), 47–66.

Appendix I Batch Registration

The objective of the batch registration is to maximize satisfy students' course request preferences subject to the number of courses and sections the university offers, classroom capacity, and physical distances between classes. Students with similar course requests are grouped together. Then, the algorithm works in 6 phases:

1. The algorithm orders students based on the number of sections available for the courses they requested and assigns course sections to them.

2. Students without a complete schedule are taken in random order and are assigned sections.

3. The algorithm randomly selects and assigns an unassigned section to students.

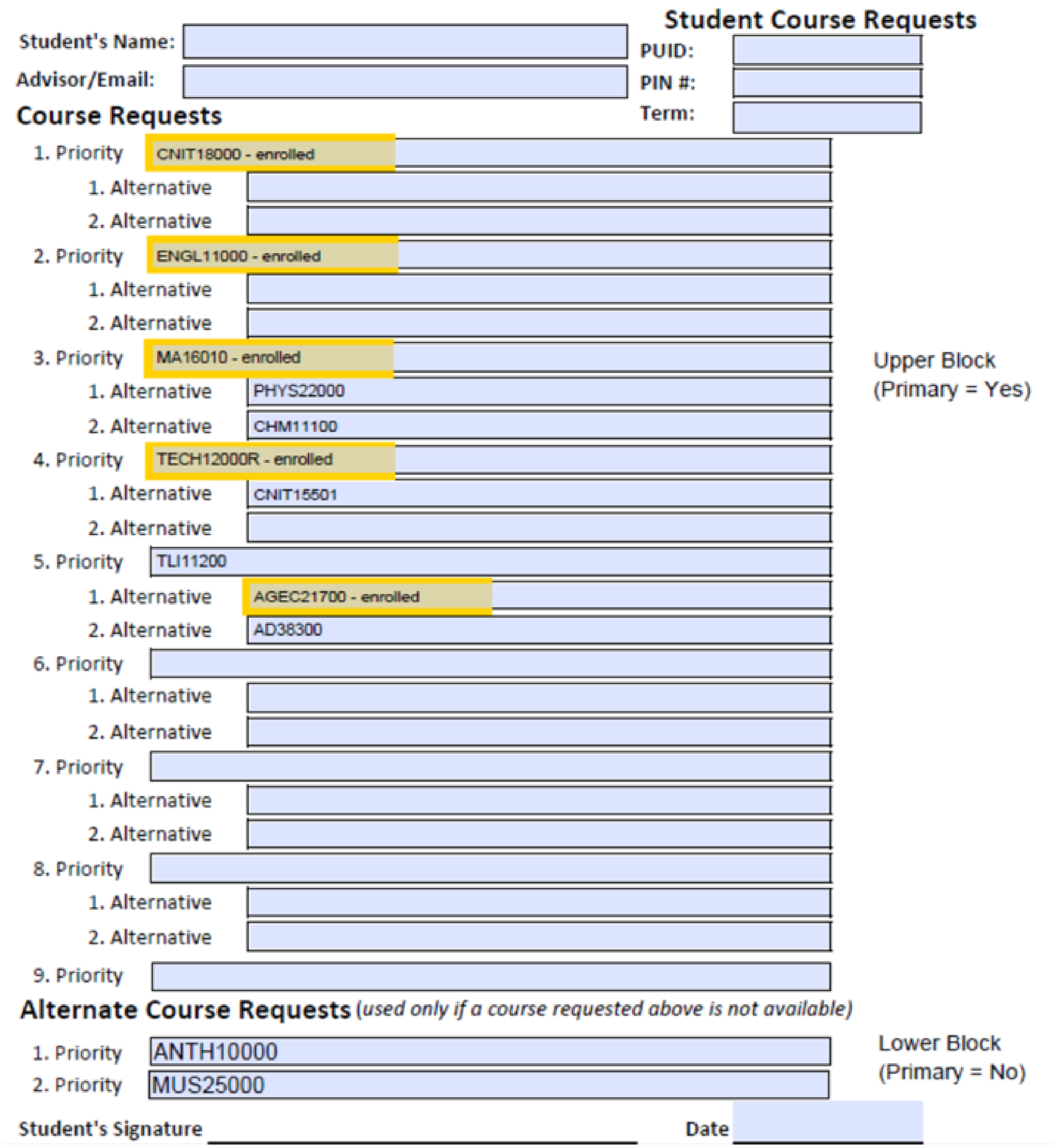
4. The algorithm improves the overall schedules by using backtracking technique.

5. Students are selected randomly and try to fill in any available sections at that point if all their requests are unassigned.

6. The algorithm goes back to step 1 and starts over again.

Interested readers can refer to (Müller & Murray, 2010) for more information about the batch registration at Purdue University. The figure below also illustrates what information students need to fill out for their course submission.

Figure A.1: Course Request Form



Student Course Requests

Student's Name:

Advisor/Email:

PUID:

PIN #:

Term:

Course Requests

1. Priority: CNIT18000 - enrolled
   1. Alternative:
   2. Alternative:
2. Priority: ENGL11000 - enrolled
   1. Alternative:
   2. Alternative:
3. Priority: MA16010 - enrolled
   1. Alternative: PHYS22000
   2. Alternative: CHM11100
4. Priority: TECH12000R - enrolled
   1. Alternative: CNIT15501
   2. Alternative:
5. Priority: TLI11200
   1. Alternative: AGEC21700 - enrolled
   2. Alternative: AD38300
6. Priority:
   1. Alternative:
   2. Alternative:
7. Priority:
   1. Alternative:
   2. Alternative:
8. Priority:
   1. Alternative:
   2. Alternative:
9. Priority:

Upper Block
(Primary = Yes)

Alternate Course Requests *(used only if a course requested above is not available)*

1. Priority: ANTH10000
2. Priority: MUS25000

Lower Block
(Primary = No)

Student's Signature ______________________ Date ________

Appendix II Student Survey

I conduct a field survey to Purdue students about their in-class experiences from an early morning and a non-early morning classes in Fall 2022. The email message about the survey and the online survey via Qualtrics are attached in the following pages. This activity has been approved (RCT ID: AEARCTR-0010038) by the AEA RCT Registry.

Dear Students from ECON 252,

I am Anthony Yim, a Purdue PhD student in economics. Dr. Victoria Prowse and I would like to invite you to participate in a research survey (IRB-2022-874).

The purpose of this survey is to help researchers understand student experiences from **ECON 252 Macroeconomics**. It will take 2-3 minutes to complete the survey. After completing the survey, you can choose to opt in to a raffle with the chance (up to 50% chance) to win gift cards.

The survey is **anonymous** and strictly **voluntary** and would not affect your course grades. Professor Vargas will not know who will participate in the survey and survey responses because collected data will not be shared with him. Dr. Prowse and I are the only people to receive and review the responses and associated Purdue emails if students choose to participate in a lottery to win a prize. Responses are not associated with emails.

If you are interested to participate in this survey, please click on the following link:

[The survey link will be posted here.]

We would also advice interested participants to take the survey outside of class time.

Please contact Anthony Yim (lyim@purdue.edu) if you have further questions.

Best wishes,

Anthony

Default Question Block

The purpose of this survey is to help researchers understand student experiences from **ECON 252 Macroeconomics**. It will take **2-3 minutes** to complete the survey. After completing the survey, you can choose to opt in to a raffle with the chance to win $5 Amazon gift cards. The survey is **anonymous** and **strictly voluntary** and **does not affect any grades** in this course.

Select the option that best describes how you feel about each statement. **Notice that the statements only focus on your experiences during class.**

ABOUT THE CLASS MEETINGS

1. I enjoy attending classes.

- ◯ Strongly Agree
- ◯ Agree
- ◯ Neither Agree or Disagree
- ◯ Disagree
- ◯ Strongly Disagree

2. I actively participate in class discussions.

- ◯ Strongly Agree
- ◯ Agree
- ◯ Neither Agree or Disagree
- ◯ Disagree

- Strongly Disagree

3. My classmates actively participate in class discussions.

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

4. Class discussions increase my critical thinking.

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

5. Classes motivate my learning.

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

6. I would learn more from a different section of ECON 252 with the same instructor.

- Strongly Agree
- Agree
- Neither Agree or Disagree

- Disagree
- Strongly Disagree

7. My experience in this class makes me want to take another economics class.

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

ABOUT THE INSTRUCTOR

8. The instructor gives clear lectures.

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

9. The instructor gives engaging lectures.

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

10. The instructor helps me learn during class.

- Strongly Agree

- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

11. The instructor is enthusiastic about the materials during class.

- Strongly Agree
- Agree
- Neither Agree or Disagree
- Disagree
- Strongly Disagree

BASIC INFORMATION

12. Your class:

- Freshman
- Sophomore
- Junior
- Senior
- Graduate
- Other

13. How would you describe yourself?

- Male
- Female
- Prefer not to answer

14. Are you of Hispanic, Latino, or of Spanish origin?

- Yes
- No
- Prefer not to answer

15. How would you describe yourself?

- American Indian or Alaska Native
- Asian
- Black or African American
- Native Hawaiian or Other Pacific Islander
- White
- Prefer not to answer

16. This course is required by your _____.

- major
- minor
- general education

17. What is your intended or declared major?

- Economics
- Business major (excluding economics)
- Other

18. Which section of ECON 252 were you **initially** assigned?

- 7:30 am - 8:20 am
- 9:30 am - 10:20 am
- Neither. I joined the course after the start of the semester.

19. Which section of ECON 252 do you actually attend?

- 7:30 am - 8:20 am
- 9:30 am - 10:20 am
- Neither of them
- Both

20. How often do you usually attend classes of ECON 252 each week?

- 0 times
- 1 time
- 2 times
- 3 times
- More than 3 times

Block 1

Would you like to enter the raffle to win a prize? Your response will still remain anonymous.

- Yes
- No

Appendix III Regression Models

After verifying that assignments to first period 7:30 AM classes are random, I can move forward with the IV estimation models to estimate the impact of early morning classes on students' education outcomes. Previously, I discussed the course registration process at Purdue University in which students can still make changes after they receive initial class schedules. Since all students are not compliers into the treatment shown in Table A.1, I test the strength of the instrument by estimating the first-stage regression with the following equation:

$$Finalized\ Early_{icpt} = \beta_0 + \gamma Assigned\ Early_{icpt} + \beta_1 S_i + \beta_2 C_{ict} + \sigma_{cpt} + \varepsilon_{icpt} \tag{4}$$

where $Finalized_{icpt}$ is an indicator for whether student i in class c with instructor p at term t enroll in an early morning class. σ is course-by-instructor-by-term fixed effect, addressing a potential concern that assignments of instructors' teaching schedules are endogenous since they are not random.

For $Assigned\ Early_{icpt}$ to be a valid instrument under the Local Average Treatment Effect (LATE) framework, there are four identification assumptions:

1. Relevance: Assigned early morning sections has a causal effect on finalized early morning sections conditional on course request preferences.

2. Independence: Assignments to early morning sections are as good as random.

3. Exclusion Restriction: Assigned early morning sections only affect the outcome variables of interest through finalized early morning sections.

4. Monotonicity: Getting assigned to early morning classes either increases the likelihood of actually enrolling in early morning classes or does nothing, but it does not decrease the likelihood of actually enrolling in early morning classes. That also means that the students are all always takers, never takers or compliers with no defiers.

Appendix IV Tables

Table A.1: Course Compliance Rates

	Course by Instructor					
	Overall	Early	Non-Early	N	Mean Diff.	P-value
STEM Sample						
	0.857	0.873	0.854	6,551	0.0190*	0.071
Major Sample						
	0.845	0.842	0.846	5,094	-0.00419	0.753

Notes: The observations in both upper and lower panels are in course-by-instructor-by-term level. The upper panel displays the compliance rates from domestic freshman cohort from Fall 2018, Fall 2019, and Spring 2020 in my STEM-course analyses. I call those observations as "STEM Sample". The lower panel displays the compliance rates from domestic freshman cohort from Fall 2018 in my major-choice analyses. I call those observations as "Major Sample". * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Student-by-Course-by-Term Level Balance Test (Alternative Specifications)

	(1)	(2)	(3)
Female	0.049**	0.005	0.006
	(0.020)	(0.010)	(0.011)
Black	-0.018	-0.010	-0.011
	(0.022)	(0.019)	(0.020)
Hispanic	-0.008	0.004	0.007
	(0.013)	(0.011)	(0.011)
Asian	-0.023*	-0.013	-0.013
	(0.013)	(0.010)	(0.011)
Other Race/Ethnicity	-0.020	-0.005	-0.005
	(0.026)	(0.024)	(0.025)
First Generation	-0.012	-0.012	-0.012
	(0.013)	(0.009)	(0.009)
Standardized SAT Combined	-0.015	-0.007	-0.006
	(0.010)	(0.005)	(0.005)
F-stat P-Value	0.173	0.122	0.142
Observations	9,626	9,626	9,626
R^2	0.008	0.224	0.226
Course-Term FE	N	Y	Y
Course Preference Controls	N	Y	Y
Number of Courses Requested FE	N	N	Y

Notes: Robust standard errors in parentheses are clustered at the individual and course-by-term levels (6,595 clusters at the individual level and 41 clusters for course-by-term level). SAT combined is a standardized variable with mean of zero and standard deviation of one. In this specification, I use the course-by-term fixed effect in this specification instead of course-by-instructor-by-term fixed effect in Table 2. Observations are domestic non-athlete freshman cohort between the age of 18 and 21 from Fall 2018, Fall 2019, and Spring 2020. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Courses in the Three Samples

Course Grade Sample			STEM Course Sample			Major Choice Sample		
Course Title	**Enrollment**	**Early AM**	**Course Title**	**Enrollment**	**Early AM**	**Course Title**	**Enrollment**	**Early AM**
Basic Aircraft Science	82	59	Basic Aircraft Science	45	33	Basic Aircraft Science	38	27
Fundamentals Of Biology I	1911	575	Fundamentals Of Biology I	1343	392	Fundamentals Of Biology I	570	183
Fundamentals Of Biology	6	2	Fundamentals Of Biology	6	2	Human Anatomy and Physiology	264	129
Human Anatomy And Physiology	777	334	Human Anatomy And Physiology	513	205	Fundamentals Of Speech Communication	608	65
Fundamentals Of Speech Communication	608	65	Macroeconomics	77	76	Macroeconomics	75	72
Macroeconomics	152	148	Functions And Trigonometry	947	115	Exploring Teaching As A Career	43	18
Exploring Teaching As A Career	43	18	Applied Calculus I	2056	162	Multiculturalism And Education	31	9
Multiculturalism And Education	31	9	Applied Calculus II	64	15	First-Year Composition	496	25
First-Year Composition	496	25	Statistics And Society	138	106	French Level III	8	2
French Level III	8	2	Functions And Trigonometry	434	48	Applied Calculus I	1019	71
Functions And Trigonometry	1376	161	Applied Calculus I	3073	233	Applied Calculus II	58	14
Applied Calculus I	3073	233	Applied Calculus II	122	29	Spanish Level III	161	5
Applied Calculus II	122	29	Spanish Level III	161	5	Spanish Level IV	25	5
Spanish Level III	161	5				Statistics And Society	133	98
Statistics And Society	271	204						

Table A.4: Mapping Between Courses and Majors

Course Title	Direct Majors	Fraction
Basic Aircraft Science	Aeronautic Engr Tech	0.68
Biology I	Biology	0.019
Human Anatomy And Physiology	Biology	0.00
Fundamentals of Speech	Communication	0.028
Macroeconomics	Economics	0.015
Exploring Teaching	Gen Education	0.022
Multiculturalism & Education	Gen Education	0.031
English Composition	English	0.013
French Level III	French	0.00
Precalculus	Mathematics	0.005
Applied Calculus I	Mathematics	0.0011
Applied Calculus II	Mathematics	0.017
Spanish Level III	Spanish	0.00
Spanish Level IV	Spanish	0.037
Statistics & Society	Statistics	0.00

Notes: Direct Majors mean the most related majors to the course. Fraction refers to the fraction of students in the course who eventually major in the corresponding major(s).

Table A.5: Mapping Between Courses and Colleges

Course Title	College	Fraction
Macroeconomics	Business	0.453
Exploring Teaching	Education	0.549
Multiculturalism & Education	Education	
Fundamentals of Speech	Liberal Arts	0.113
English Composition	Liberal Arts	
French Level III	Liberal Arts	
Spanish Level III	Liberal Arts	
Spanish Level IV	Liberal Arts	
Basic Aircraft Science	Polytechnic Institute	0.947
Biology I	Science	0.0641
Human Anatomy And Physiology	Science	
Precalculus	Science	
Applied Calculus I	Science	
Applied Calculus II	Science	
Statistics & Society	Science	

Notes: College is the place that offers the course. Fraction refers to the fraction of students in the course who eventually choose a major from the corresponding college.

Table A.6: Effect on Standardized Course Grades

	Panel 1: 2SLS Estimates		
	(1)	(2)	(3)
Assigned 7:30 AM Section	-0.0782	-0.0616	-0.0611**
	(0.0502)	(0.0420)	(0.0274)
Course-Instructor-Term FE	Y	Y	Y
Course Request Controls	N	Y	Y
Demographic Controls	N	N	Y
N	9,020	9,020	9,020
	Panel 2: OLS Estimates		
	(1)	(2)	(3)
Assigned 7:30 AM Section	-0.0667	-0.0503	-0.0533**
	(0.0425)	(0.0349)	(0.0225)
Course-Instructor-Term FE	Y	Y	Y
Course Request Controls	N	Y	Y
Demographic Controls	N	N	Y
N	9,020	9,020	9,020
R^2	0.119	0.123	0.234

Notes: Observations are domestic non-athlete freshman cohort between the age of 18 and 21 from Fall 2018, Fall 2019, and Spring 2020. There are 78 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. Robust standard errors in parentheses are clustered at the individual and course-by-term levels (5,029 clusters at the individual level and 311 clusters for section-by-term level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Descriptive Statistics of the Field Survey

	Initial Assignment		Actual Assignment		
	Early AM	Non-Early AM	Early AM	Non-Early AM	Neither
Freshman	0.451	0.0536	0.477	0.0773	0.000
	(0.499)	(0.226)	(0.501)	(0.268)	(0.000)
Sophomore	0.349	0.655	0.329	0.641	0.571
	(0.478)	(0.477)	(0.471)	(0.481)	(0.535)
Junior	0.171	0.256	0.161	0.249	0.429
	(0.378)	(0.438)	(0.369)	(0.433)	(0.535)
Senior	0.0229	0.0298	0.0258	0.0276	0.000
	(0.150)	(0.170)	(0.159)	(0.164)	(0.000)
Graduate	0.000	0.00595	0.000	0.00552	0.000
	(0.000)	(0.0772)	(0.000)	(0.0743)	(0.000)
Other	0.00571	0.000	0.00645	0.000	0.000
	(0.0756)	(0.000)	(0.0803)	(0.000)	(0.000)
Female	0.251	0.482	0.252	0.464	0.286
	(0.435)	(0.501)	(0.435)	(0.500)	(0.488)
Male	0.746	0.512	0.742	0.530	0.714
	(0.438)	(0.501)	(0.439)	(0.500)	(0.488)
Gender-Not Disclosed	0.00571	0.00595	0.00645	0.00552	0.000
	(0.0756)	(0.0772)	(0.0803)	(0.0743)	(0.000)
White	0.64	0.649	0.645	0.657	0.286
	(0.481)	(0.479)	(0.480)	(0.476)	(0.488)
Black	0.04	0.0298	0.0452	0.0276	0.000
	(0.197)	(0.170)	(0.208)	(0.164)	(0.000)
Asian	0.246	0.25	0.226	0.249	0.714
	(0.432)	(0.434)	(0.419)	(0.433)	(0.488)
Islander	0.00571	0.000	0.00645	0.000	0.000
	(0.0756)	(0.000)	(0.0803)	(0.000)	(0.000)
Race-Not Disclosed	0.0686	0.0655	0.0774	0.0608	0.000
	(0.253)	(0.248)	(0.268	(0.240)	(0.000)
Hispanic	0.0571	0.0952	0.0516	0.0994	0.000
	(0.233)	(0.294)	(0.222)	(0.300)	(0.000)
Non-Hispanic	0.914	0.893	0.916	0.890	1.00
	(0.281)	(0.310)	(0.278)	(0.314)	(0.000)
Hispanic-Not Disclosed	0.0286	0.0119	0.0323	0.0110	0.000
	(0.167)	(0.109)	(0.177)	(0.105)	(0.000)
General Edu.	0.246	0.155	0.258	0.155	0.143
	(0.432)	(0.363)	(0.439)	(0.363)	(0.378)
Major	0.634	0.690	0.645	0.691	0.286
	(0.483)	(0.464)	(0.480)	(0.464)	(0.488)
Minor	0.114	0.155	0.0903	0.155	0.571
	(0.319)	(0.363)	(0.288)	(0.363)	(0.535)
Business (excl. Econ)	0.326	0.488	0.323	0.481	0.286
	(0.470)	(0.501)	(0.469)	(0.501)	(0.488)
Economics	0.0971	0.0357	0.0968	0.0442	0.000
	(0.297)	(0.186)	(0.297)	(0.206)	(0.000)
Other Majors	0.577	0.476	0.581	0.475	0.714
	(0.495)	(0.501)	(0.495)	(0.501)	(0.488)
Attend = 0	0.0114	0.0238	0.000	0.0110	0.571
	(0.107)	(0.153)	(0.000)	(0.105)	(0.535)
Attend = 1	0.0343	0.0357	0.0194	0.0387	0.286
	(0.182)	(0.186)	(0.138)	(0.193)	(0.488)
Attend = 2	0.194	0.167	0.194	0.171	0.143
	(0.397)	(0.374)	(0.397)	(0.378)	(0.378)
Attend = 3	0.754	0.774	0.781	0.779	0.000
	(0.432)	(0.420)	(0.415)	(0.416)	(0.000)
Attend > 3	0.00571	0.000	0.0803	0.000	0.000
	(0.0756)	(0.000)	(0.0803)	(0.000)	(0.000)
N	175	168	155	181	7

Notes: The observations are in student level. This table refers to the regression results in Table 6. Standard deviation is in parentheses.

Table A.8: Effect of Assigned Early Morning Classes on Students' Class Experiences

	Strongly Agree (1)	Agree or Above (2)	Neither or Above (3)	Disagree or Above (4)
About the Class Meetings				
Class Participation	-0.0115	-0.124**	-0.0183	-0.0291
	(0.0337)	(0.0518)	(0.0628)	(0.0350)
Classmate Participation	0.0762**	-0.00835	-0.105*	-0.00249
	(0.0335)	(0.0635)	(0.0574)	(0.0276)
Increase Critical Thinking	0.0442	-0.0220	-0.0318	0.0166
	(0.0460)	(0.0622)	(0.0412)	(0.0243)
Class Motivate Learning	0.0282	-0.0966*	-0.00175	0.0181
	(0.0508)	(0.0560)	(0.0364)	(0.0207)
Learn More in Diff. Section with same instructor	0.116***	0.247***	0.172***	0.0744*
	(0.0382)	(0.0548)	(0.0622)	(0.0394)
About Student Interest in Economics				
Enjoy Attending Classes	-0.0114	-0.104*	-0.0237	-0.00475
	(0.0445)	(0.0595)	(0.0388)	(0.0196)
Desire Another Econ Course	0.0369	0.0418	0.0620	-0.0214
	(0.0449)	(0.0596)	(0.0462)	(0.0277)
About Instructor				
Clear Lecture	-0.0327	0.0178	0.0224	-0.00889
	(0.0617)	(0.0335)	(0.0176)	(0.00909)
Engaging Lecture	-0.0270	-0.0531	-0.00129	-0.00634
	(0.0588)	(0.0541)	(0.0323)	(0.0205)
Instructor Help Learning	-0.0647	0.00482	0.00379	-0.00891
	(0.0578)	(0.0478)	(0.0185)	(0.00911)
Instructor Enthusiastic	-0.104*	-0.0404	-0.00338	-0.00889
	(0.0616)	(0.0403)	(0.0164)	(0.00909)
Student School Year FE	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y
N	343	343	343	343

Notes: Observations are students from ECON 25200 course in Fall 2022. There are two sections (7:30 AM and 9:30 AM) taught by the same instructor. The treatment variables are indicators for whether students answer "Strongly Agree", "Agree", "Neither Agree or Disagree", and "Disagree" from columns (1) to columns (4). ECON 25200 is an introductory macroeconomics course offered by the Krannert School of Management at Purdue University. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Effect of Assigned Early Morning Classes on Freshman Students' Class Experiences

	Panel 1				
	Class Participation (1)	Classmate Participation (2)	Increase Critical Thinking (3)	Class Motivate Learning (4)	Learn More in Diff. Section (5)
Assigned 7:30 AM Section	-0.554***	-0.0603	-0.214	-0.0898	-0.00463
	(0.182)	(0.185)	(0.167)	(0.111)	(0.160)
Student School Year FE	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y
N	88	88	88	88	88
R^2	0.285	0.217	0.224	0.207	0.367
Dependent Variable Mean	0.307	0.511	0.625	0.761	0.420

	Panel 2					
	Clear Lecture (1)	Engaging Lecture (2)	Instructor Help Learning (3)	Instructor Enthusiastic (4)	Enjoy Attending Classes (5)	Desire Another Econ Course (6)
Assigned 7:30 AM Section	0.176	-0.0722	0.314*	0.114	-0.264**	0.113
	(0.118)	(0.127)	(0.177)	(0.132)	(0.117)	(0.186)
Student School Year FE	Y	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y	Y
N	88	88	88	88	88	88
R^2	0.184	0.175	0.276	0.210	0.197	0.277
Dependent Variable Mean	0.932	0.761	0.864	0.864	0.716	0.557

Notes: Observations are freshman students from ECON 25200 course in Fall 2022. There are two sections (7:30 AM and 9:30 AM) taught by the same instructor. The dependent variables are indicators for whether students answer "Strongly Agree" and "Agree." Columns (1), (2), (3), (4), and (5) of Panel 1 are outcomes related to student's learning; columns (1), (2), (3), and (4) of Panel 2 are outcomes related to the course instructor, and columns (5) and (6) of Panel 2 are outcomes related to student's interest on the course subject. ECON 25200 is an introductory macroeconomics course offered by the Krannert School of Management at Purdue University. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: Effect on Corresponding STEM Courses in the Next Term

	Panel 1: 2SLS Estimates		
	(1)	(2)	(3)
Assigned 7:30 AM Section	-0.0318	-0.0403*	-0.0415**
	(0.0214)	(0.0208)	(0.0204)
Course-Instructor-Term FE	Y	Y	Y
Course Request Controls	N	Y	Y
Demographic Controls	N	N	Y
N	5,118	5,118	5,118
Dependent Variable Mean	0.205	0.205	0.205
	Panel 2: Reduced Form Estimates		
	(1)	(2)	(3)
Assigned 7:30 AM Section	-0.0271	-0.0357**	-0.0353**
	(0.0185)	(0.0178)	(0.0177)
Course-Instructor-Term FE	Y	Y	Y
Course Request Controls	N	Y	Y
Demographic Controls	N	N	Y
N	5,118	5,118	5,118
R^2	0.044	0.055	0.057
Dependent Variable Mean	0.205	0.205	0.205

Notes: Observations are domestic non-athlete freshman cohort between the age of 18 and 21 from Fall 2018, Fall 2019, and Spring 2020 in my STEM-course analyses. There are 61 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. Robust standard errors in parentheses are clustered at the individual and section-by-term levels (4,088 clusters at the individual level and 166 clusters for section-by-term level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.11: Heterogeneous Effect on Taking Corresponding STEM Courses in the Next Term

	(1)	(2)	(3)	(4)	(5)
7:30 AM Section	-0.0353**	-0.000877	-0.0256	-0.0390**	-0.0389**
	(0.0177)	(0.0304)	(0.0196)	(0.0168)	(0.0169)
Female × 7:30 AM Section		-0.0496*			
		(0.0293)			
Black × 7:30 AM Section			-0.0151		
			(0.0715)		
Hispanic × 7:30 AM Section			-0.0342		
			(0.0363)		
Asian × 7:30 AM Section			-0.0820*		
			(0.0455)		
Other × 7:30 AM Section			0.123		
			(0.141)		
Standardized SAT × 7:30 AM Section				-0.0175	
				(0.0157)	
1st Gen Student × 7:30 AM Section					0.0182
					(0286)
Course-Instructor-Term-term FE	Y	Y	Y	Y	Y
Course Request Controls	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y
N	5,118	5,118	5,118	5,118	5,118
R^2	0.057	0.058	0.058	0.057	0.057
Dependent Variable Mean	0.205	0.205	0.205	0.205	0.205

Notes: Observations are domestic non-athlete freshman cohort between the age of 18 and 21 from Fall 2018, Fall 2019, and Spring 2020. There are 61 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. In column (4), I use white students as the reference group, and Other refers to Native American students and students with non-disclosure ethnicity. Robust standard errors in parentheses are clustered at the individual and course-by-term levels (4,088 clusters at the individual level and 166 clusters for section-by-term level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$