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

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February 19, 2025

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 35% reduction in pursuing the major within the same college and a 22% rise in choosing a low-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, Lars Lefgren, 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 APPAM, 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.

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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). While the detrimental effects of early morning class schedules on academic performance are well-established, their impact on academic trajectories and labor market outcomes remains less understood. This paper contributes by exploring these underexamined dimensions, providing new insights into the broader implications of early class schedules.

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 0.07 GPA points, a 20% reduction in the probability of future STEM course enrollment, and a 35% 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 low-earning major by 22%. The primary influence of graduating from a low-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.

This paper contributes to the literature on how shocks in early education affect long-term academic and career choices. Prior research has examined various disruptions—such as the gender of an introductory professor, peer composition, and major sequencing—that influence students' long-term academic outcomes. My findings suggest that the "shock" of being assigned to an early morning class can be just as consequential. For example, Carrell *et al.* (2010) find that female students assigned to a female professor in introductory STEM courses are 26 percentage points more likely to persist in STEM majors than those assigned to male professors. Similarly, Anelli *et al.* (2023) show that an increase in the proportion of foreign-born peers in an introductory math course reduces domestic students' STEM persistence by 4.7 percentage points. My results indicate that early morning class assignment lowers the probability of future STEM course enrollment by 5.2 percentage points and decreases the likelihood of majoring in STEM fields by 3.8 percentage points—effects of a similar magnitude. While peer and faculty effects play a critical role in shaping students' academic trajectories, my findings highlight that structural constraints, such as course scheduling, can also have substantial and lasting consequences on students' major choices.

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 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. Unlike military settings, where students have limited course choice and strict attendance policies, students at my studied institution may react to early morning courses by disengaging, skipping class, or under-performing, leading to significant shifts in their academic trajectories. This suggests that institutional flexibility amplifies the impact of negative academic shocks. 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

[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.

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.

Furthermore, my findings align with research on how early academic experiences shape major selection. Patterson *et al.* (2023) document that students are 39% more likely to graduate in a subject they were assigned to during their first semester of their sophomore year, highlighting the lasting influence of initial exposure. While their study demonstrates how early exposure reinforces major selection, my findings reveal a parallel but inverse effect—being assigned to an early morning course discourages students from persisting in that major. Specifically, I find that early morning class assignment leads to a 43% (or 3.8 percentage point) reduction in the likelihood of majoring in STEM fields and a 35% (or 0.037 percentage point) reduction in the probability of choosing a major from the same college. This contrast suggests that while early exposure can reinforce major selection, unfavorable course conditions—such as inconvenient scheduling—can deter students from persisting in their intended academic paths.

In addition, Bleemer (2022) finds that after Proposition 209, URM students faced a 4.3 percentage point decline in bachelor's degree attainment and a 5% reduction in average wages, illustrating the long-term economic consequences of changes in educational pathways. Similarly, Bleemer & Mehta (2022) show that failing to meet the GPA requirement for an economics major results in a 46% decrease in annual early-career wages. While Anelli *et al.* (2023) find that domestic students who leave STEM majors due to increased foreign peer presence tend to shift into business majors—fields with relatively high earning potential—effectively offsetting negative wage impacts, my findings suggest a different pattern. Students assigned to early morning classes are 22% more likely to graduate with a low-earning major, indicating that rather than pivoting to another high-earning field, they are more likely to move into majors with significantly lower financial returns.

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

The circadian rhythm, a hard-wired "clock" in the brain, controls the production of melatonin, which induces sleep. During adolescence, teenagers experience significant changes of the circadian rhythm. In fact, melatonin production typically starts around 11 PM and peaks until 7 AM, which contrasts with adult patterns. Hence, this makes early morning classes for teenagers (such as 7:00 AM) equivalent to asking adults to attend work meetings at 4:00 AM (Carrell *et al.*, 2011). Studies show that an individual's ability to learn fluctuates based on their circadian rhythm, which makes early morning class times misaligned with young students' biological clocks (Goldstein *et al.*, 2007; Schmidt *et al.*, 2007; Pope, 2016).

To understand how early morning classes affect students' decision-making and educational outcomes, we must first review the literature on the impact of start time on academic performance as well as the broader research on students' academic achievements, particularly regarding grades, STEM persistence, and the labor-market consequences of their chosen majors.

2.1 Impact of Start Time on Academic Outcomes

This study examines the impact of early morning classes on key academic and labor market outcomes at a large public university in the U.S. by exploiting the random assignment of courses to students. The institutional context of this study offers a more typical comparison to the broader university student population in the U.S. Previous studies have indicated

that early morning classes negatively affect academic performance. Carrell *et al.* (2011) find that cadets at the United States Military Academy (USMA) assigned to early morning classes earn lower grades than those with later schedules. Similarly, Williams & Shapiro (2018) reports that students at the United States Air Force Academy perform better on tests in the afternoon compared to their peers in the morning. Regarding major selection, Haggag *et al.* (2021) found that attending early morning classes decreased the likelihood of students choosing majors aligned with those courses at USMA. My research adds new insights, showing that early morning classes increase the likelihood of graduating with a degree in a low-earning major.

Research on the effects of start times extends beyond university students. In K-12 education, later school start times have been linked to improved academic performance. 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 North Carolina. Similarly, Groen & Pabilonia (2019) show that starting high school an hour later improves reading test scores for female students even though the authors find no evidence for higher test scores from male students. Pope (2016) further investigates the impact of class timing on students' productivity and suggests that students' GPAs improve when math or English classes are held in the morning rather than the afternoon.

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

2.2 Grades, STEM Persistence, and Labor-Market Consequences of Majors

In this study, I explore three key relationships: the impact of early morning classes on grades, how these classes influence course-taking behaviors and major selection. College majors have significant effects on long-term earnings, career trajectories, and lifestyles (Altonji *et al.*, 2012, 2014; Bleemer & Mehta, 2022; Chevalier, 2011; Hastings *et al.*, 2013; Kirkeboen *et al.*, 2016; Patnaik *et al.*, 2020; Webber, 2014b), leading to considerable policy efforts aimed at guiding students toward high-return majors (Chevalier, 2011; Altonji *et al.*, 2012; Hastings *et al.*, 2013; Webber, 2014b; Altonji *et al.*, 2014; Kirkeboen *et al.*, 2016; Patnaik *et al.*, 2020; Bleemer & Mehta, 2021, 2022; Denning & Turley, 2017; Sjoquist & Winters, 2015). Moreover, recent evidence indicates that barriers to accessing high-return majors and popular courses can have negative consequences for disadvantaged and female students (Bleemer, 2021; Bleemer & Mehta, 2023; Mumford *et al.*, 2024). My study suggests that early morning classes significantly influence students' major decisions. To the best of my knowledge, this is the first study to provide causal evidence that early morning classes reduce the likelihood of students majoring in STEM fields while increasing the probability of choosing low-earning majors. These findings may stem from the fact that early morning classes lower students' test scores, which in turn reduces their likelihood of enrolling in STEM-related courses in subsequent semesters—a relationship this study also explores.

Our findings add to the expanding research on the factors that shape college major decisions. While previous studies have identified student preferences, anticipated earnings, peer influence, academic ability, and financial considerations as important determinants of major choice (Wiswall & Zafar, 2014; Patnaik *et al.*, 2020; Elsner *et al.*, 2021; Zölitz & Feld, 2021), recent work points to the importance of smaller, often overlooked factors. Changes such as the time of day that a class is offered (Haggag *et al.*, 2021), the likelihood of enrolling in certain courses (Mumford *et al.*, 2024), or the semester a course is taken (Patterson *et al.*, 2021) can also have significant impacts on students' major choice and university experiences.

This paper shows that early morning classes can significantly influence students' major decisions, revealing that even minor scheduling shifts can lead to significant changes in their overall university experience and potentially influence long-term labor market outcomes.

3 Institutional Setting & Assignment Algorithm

3.1 Institutional Setting

Purdue is a large public university in the U.S. with a 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.[2] 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.[3]

Courses and sections are closely related but distinct concepts in this paper. A course refers to the overall structure of a subject, encompassing the curriculum, learning objectives, and content (e.g., ECON 252 - Macroeconomics and ENGL 10600 - First-Year Composition). A section, however, specifies a particular offering of that course, including details such as the location, meeting times, meeting dates, and assigned instructor. For example, the course ECON 252 may have two sections—Section 1 meeting at 7:30 AM with Professor Yim in

[2]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. However, it is important to note that the distribution of introductory courses offered by various colleges does not necessarily align with the distribution of students' enrolled majors in this study as my sample is limited to lower-year students with randomly assigned schedules who enrolled in lower-division (100 and 200 level) courses. It is also worth noting that some colleges offered more early morning courses (7:30 a.m.) than others did.

[3]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.

Room A, and Section 2 meeting at 11:30 AM with the same Professor Yim in Room B. Each section represents a unique logistical instance of the same course material. While the course remains the same across all sections, the sections provide additional information about when and where the course is delivered and by whom.

3.2 Course Assignment Algorithm

The Purdue class assignment algorithm is called the batch registration, which was reintroduced in 2018.[4] The university randomly assigns class schedules to undergraduate students through this algorithm conditional on their course request preferences.[5] The algorithm incorporates the individual course preference rankings as inputs to produce schedules for all students.[6] 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

[4]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.

[5]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. See Appendix I for a detailed description of the course assignment algorithm.

[6]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.

request strategies, students submit their course requests in the hope that they receive their most preferred schedule.[7] 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 submitting their course request.[8] However, most freshman students do not state their preferred class times because they are unaware of this feature in the course request form.

4 Data and Sample

The data for this study comes from Purdue University in West Lafayette, Indiana, and consists of 9,020 student-by-course-by-term observations from Fall 2018 and Fall 2019. The main sample includes non-athlete students who are assigned to general education or introductory courses with multiple sections taught by the same professor, including at least one early morning class.

Table 1 outlines the stepwise construction of my main analysis sample. Column 1 presents the full population of freshmen students with 71,435 student-by-course-by-term observations. Column 2 narrows this to 52,250 observations from freshmen assigned to the batch registration system. Column 3 further refines the sample to 50,196 observations, focusing on non-athlete students taking lower-level courses and aged 18 to 21. Finally, Column 4 represents the primary analysis sample of 9,020 observations, which consists of students assigned to courses that meet the study's criteria for comparison—namely, courses with multiple sections taught by the same instructor, where at least one section is scheduled as an early morning class.[9]

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

[8]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.

[9]While the main sample (column 4 of Table 1) differs slightly from the full freshman population (column

Using the overall sample of 9,020 observations, I first estimate how attending early morning classes affects the course grades students received from the early morning classes they attended. This analysis focuses on all non-athlete students in the dataset and examines their performance within the specific courses where they were randomly assigned to early morning class sections. This provides a foundational understanding of the potential immediate impact of early morning class assignments on academic outcomes.

To further investigate other important student outcomes, I focus on specific subsamples. First, to estimate how early morning classes affect students' likelihood of taking more STEM courses within the subsequent year, I use a subsample of 5,118 student-by-course-by-term observations. This subsample is restricted to non-athlete freshman students between the ages of 18 and 21 years old, drawn from the larger main sample. The sample size shrinks from 9,020 to 5,118 because this analysis focuses specifically on the Fall 2018 and Fall 2019 cohorts. These two cohorts are ideal for the analysis as they are the only groups within the main sample for which I can observe students' future course-taking behavior over multiple terms. This allows for a detailed examination of how early morning class assignments influence subsequent enrollment in STEM courses. [10]

Second, to analyze the effect of early morning classes on students' choice of major, I draw on a subsample of 3,912 student-by-course observations from the Fall 2018 cohort within the main sample. This cohort is ideal for the analysis because it is the only group in which graduating majors can be observed. Furthermore, these non-athlete freshman students were the first class impacted by Purdue's class schedule randomization policy.

Finally, to estimate the effect of early morning classes on students' future college major

1) in certain characteristics—having a higher proportion of female (56.5% vs. 45.1%) and white students (73.2% vs. 62.1%), a slightly lower average SAT score (1,249 vs. 1,283), and a greater share of first-generation students (18.4% vs. 11.8%)—it still represents a meaningful subset of Purdue's undergraduate population. The sample primarily consists of students enrolled in large, introductory, or general education courses, which are foundational across many academic disciplines. Moreover, because early morning courses are a common feature of university scheduling, the insights gained from this study remain relevant for broader discussions on class scheduling and academic performance in higher education.

[10]The Spring 2019 data are excluded because Purdue did not randomly assign students to class schedules during that term.

earnings, I rely on a subsample of 3,856 observations. Similar to the major choice analysis, this sample is derived from the Fall 2018 freshman cohort, as this group provides the necessary data to connect early class assignments to longer-term outcomes. The subsample size decreases from 3,912 to 3,856 due to a few missing values for college major earnings in the data. Despite this slight reduction, the subsample remains representative for analyzing the relationship between early class assignments and future earning potential.

Regarding the identification strategy, I compare students assigned to early morning classes with those assigned to later sections. To ensure a valid comparison, I focus exclusively on courses that have multiple sections taught by the same professor during the same semester, where at least one section is scheduled as an early morning class (7:30 AM).

This approach is a crucial component of the identification strategy. By comparing student outcomes within the same course (e.g., Econ 100) and semester, taught by the same professor (e.g., Professor Yim), I can isolate the effect of being assigned to an early morning section (e.g., Section 1 at 7:30 AM) versus a later section (e.g., Section 2 at 11:30 AM). Consequently, incorporating course-by-instructor-by-semester fixed effects is essential for my model specifications to establish robust causal inferences. In the data, the main sample includes 60 course-by-instructor-by-semester fixed effects, while the "Subsample - STEM Courses" consists of 38 such fixed effects. Additionally, the "Subsample - Major" incorporates 39 course-by-semester fixed effects.

Table 2 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. 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.[11]

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

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.[12] 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.[13] Figure A.1 in the appendix illustrates the course request form each undergraduate student needs to fill out.

I will now outline the course registration timeline at Purdue University, using Figure 1 as a guide. On the designated Registration Day during summer break (July 5), students submit their course requests to the university. Initial course assignments are then provided on Batch Day (July 21), approximately one month before the start of the term. However, students may not receive their preferred courses or schedules. To address this, the university offers a schedule adjustment period during which students can add, drop, or switch courses and class times until the add/drop deadline (September 1), typically one week into the term. After this deadline, schedules are finalized, although students still have the option to withdraw from courses, with withdrawals noted on their transcripts. Final grades are assigned after the completion of all final exams and projects, which conclude on the last day of the term's final week (December 15).[14]

[12] 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.

[13] 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.

[14] It is worth noting that while most students receive traditional letter grades on a 4.0 scale, a small number are graded on a pass/fail basis for certain courses.

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 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.

4.3 Outcome Variables

This subsection defines the key outcome variables used in the analysis, which measure different aspects of students' academic decisions and potential future outcomes. These variables provide insight into how early morning class assignments impact students' educational trajectories.

The first outcome variable is *final course grades*, measured on a 4.0 GPA scale. These grades are assigned at the end of the term and serve as an initial measure of the effect of early morning classes on students' human capital accumulation. While final grades may contain measurement errors due to potential adjustments by instructors, they remain the most relevant indicator of student learning. Additionally, final course grades may serve as a mechanism influencing students' subsequent course-taking behavior and major choices. On average, students in the sample have a mean GPA of 3.00 with a standard deviation of 1.00.

The second outcome variable is an *indicator for whether students take STEM classes within the next two terms*. STEM classes are defined as courses offered by departments affiliated with STEM disciplines. These affiliations are determined by university administrators and faculty based on the science, technology, engineering, or mathematics intensity of the

majors offered. The classification aligns with the U.S. Department of Homeland Security's STEM Designated Degree Program List. This variable provides insights into students' persistence in acquiring STEM-related skills, which are associated with higher future earnings. In the sample, 26% of students enrolled in STEM courses within two terms, with a standard deviation of 44%.

The third outcome variable is an *indicator for whether students choose a major that is directly related to their assigned early morning course at the college level*. This variable examines whether students select a major aligned with a 7:30 AM course to which they were assigned. For instance, students assigned to an early morning calculus course are tracked to determine if they later choose a major within the same college offering the mathematics course. A detailed mapping between courses and their corresponding majors is provided in Table A.3. This variable is particularly useful for testing attribution bias as a potential mechanism, as highlighted in Haggag *et al.* (2021). In this sample, 10.4% of students selected a corresponding major at the college level, with a standard deviation of 30.6%.

Finally, the fourth outcome variable is an *indicator for whether students graduate from a low-earning major*, defined as a major with earnings in the bottom quartile of the earnings distribution. Earnings data for specific majors are sourced from Purdue's CCO and categorized into four groups based on the major-earnings distribution: first quartile ($Pr(Y_i \leq Q_{.25})$), second quartile ($Pr(Q_{.25} \leq Y_i \leq Q_{.5})$), third quartile ($Pr(Q_{.5} \leq Y_i \leq Q_{.75})$), and fourth quartile ($Pr(Q_{.75} \leq Y_i \leq Q_{.1})$). This variable highlights the potential long-term financial outcomes associated with students' major choices. On average, the median college major earnings are \$51,736, with a standard deviation of \$12,304.

Summary statistics for these outcome variables, including means and standard deviation, are included in Table 3. These provide a baseline understanding of the data and aid in interpreting the results of the analysis.

5 Empirical Strategy

I exploit a natural experiment at Purdue University. My empirical approach leverages Purdue's course assignment algorithm, which allocates course schedules based on student preferences and scheduling constraints (see Appendix I for a detailed description of the course assignment algorithm). While this process introduces randomness in class time assignment, it is crucial to account for the role of student preferences in determining early morning class placements. Specifically, students with similar course requests may face different probabilities of being assigned to an early morning (7:30 AM) section due to variations in course availability and prioritization mechanisms.

To address concerns about the independence assumption, I adopt an approach used by the school choice lottery literature (Abdulkadiroğlu *et al.*, 2011; Dynarski *et al.*, 2018). Specifically, I build on the empirical strategy of risk set fixed effect approach by estimating the probability that each course request results in an early morning class assignment and incorporating it as a control variable. This probability, referred to as the "expected treatment" by Borusyak & Hull (2023), is derived from 100 simulations of Purdue's course assignment algorithm for Fall 2018 and Fall 2019. These simulations capture the stochastic nature of course assignment while accounting for systematic, nonrandom factors such as students' priority rankings.

Then, I integrate the simulated early morning (or 7:30 AM) section probabilities into my empirical framework as follows. I group each student-course observation into discrete "risk sets" (or bins) based on the simulated early morning section probabilities in my instrumental variable specification, described shortly. This ensures that comparisons occur among students with similar course preferences and assignment likelihoods. This method, introduced by Borusyak & Hull (2023) as the control function approach, strengthens the internal validity of the independence assumption by ensuring that variation in early morning class assignment is primarily driven by the quasi-random component of the batch registration process rather than systematic differences in student preferences. Once I control for

the simulated probability of early morning section assignment, the assignment to an early morning class is as good as random and uncorrelated with student characteristics.

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).[15] 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: randomization and instrumental variable.

5.1 Randomization

To further support the independence assumption as discussed previously, I conduct balance tests examining whether observed student characteristics differ systematically across assigned early morning sections. I find no significant differences for students' demographic variables with joint F-test p-values greater than 0.1. This reinforces the argument that the variation in early morning class assignment is as good as random after conditioning on risk set fixed effects. A more detailed discussion of these findings follows in the subsequent paragraphs.

One key identification assumption is that assignments to early morning classes are random, conditional on simulated early morning section probability. To test this, I regress an indicator variable for whether students are assigned to early morning classes on a vector of students' observable characteristics, including gender, race, standardized SAT scores, first-generation status, and domestic student status, while controlling for course-by-instructor-

[15]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.

by-term fixed effects and simulated early morning section probability fixed effects.[16] The regression model is as follows:

$$Assigned\ Early_{icpt} = \delta_0 + \delta_2 S_i + Early\ Morning\ Probability\ Bin_{ict} + \sigma_{cpt} + \epsilon_{icpt} \quad (1)$$

where $Assigned\ Early_{icpt}$ indicates whether students i in course c with instructor p at term t get randomly assigned to early morning classes. S_i is a vector of students' observable characteristics. $Early\ Morning\ Probability\ Bin_{ict}$ is the simulated probability bin that student i will be assigned to an early morning section from course c. 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.

Table 4 presents the results from equation (1). In column 1, I regress an indicator for assignment to a 7:30 AM class on students' observable characteristics, excluding course request controls and course-by-instructor-by-term fixed effects. Although one out of eight characteristics differs at the 10% significance level, overall, student observables remain balanced across early morning and other class periods, as indicated by an F-test p-value of 0.374.

In column 2, after incorporating course-by-instructor-by-term fixed effects, balance improves further, with no individual characteristics differing significantly at the 5% level and a joint F-test p-value of 0.381. Column 3 introduces additional controls, including course preference indicators and a fixed effect for the total number of courses requested, leading to an increase in the joint F-test p-value to 0.424.[17] By incorporating these variables, I

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

[17] To enhance transparency in addressing potential confounding factors, I incorporate a comprehensive set of course request controls in my alternative specification. These controls capture key aspects of students' enrollment decisions, including the ranking of each course request, the total number of credits requested in a given semester, and an indicator for whether students specified preferred course times. Additionally, course request preferences include the number of requested courses, the presence of alternative course options (if the initially requested courses were not granted), and indicators for both preferred and required class times (distinguishing between 7:30 AM and non-7:30 AM sections). All course request controls are indicator variables. I also explicitly state which class times students request and create different interaction terms between each course request control variable. Estimated results of both specifications are similar.

account for systematic differences in students' course selection behavior that may influence their likelihood of being assigned to an early morning class. However, since the risk set fixed effects method serves as the primary empirical strategy in this study, I focus on reporting results based on this preferred approach for my main findings. While alternative specifications yield consistent estimates, all subsequent discussions will center on the results obtained using the risk set fixed effects framework. Finally, replacing these course preference controls and course request fixed effects with simulated early morning section probability fixed effects further strengthens balance, raising the joint F-test p-value to 0.539 in column 4. Altogether, columns 1, 2, 3, and 4 of Table 4 suggest that students' assignments to early morning classes are conditionally random with F-test p-values greater than 0.1.

As outlined in Abadie *et al.* (2023), standard errors should be clustered at the level where randomization occurs. In this study, randomization occurs at both the individual and course-semester levels. The university employs a batch algorithm to assign course schedules to students and, within each schedule, randomly assigns course sections, using course-level requests across students as a tiebreaker. Given the limited number of courses available for clustering, particularly when analyzing the major choice specifications with only one semester of cohorts, I cluster the standard errors at both the student level and the section-by-term level. This methodology is consistent with the clustering approach employed in Haggag *et al.* (2021).[18]

5.2 Instrumental Variable

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

[18]The results of these alternative specifications by clustering at the student and course-by-term levels are shown in Table A.1, and the results are well-balanced.

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 (2), 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.[19] 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:

$$Y_{icpt} = \beta_0 + \beta_1 \textit{Finalized Early}_{icpt} + \beta_2 S_i + \textit{Early Morning Probability Bin}_{ict} + \sigma_{cpt} + \varepsilon_{icpt} \quad (2)$$

where Y_{icpt} indicates the education outcomes of students. $\textit{Finalized Early}_{icpt}$ 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, and first generation status. $\textit{Early Morning Probability Bin}_{ict}$ is the simulated probability bin that student i will be assigned to an early morning section from course c. 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 indicator variable for whether students get randomly assigned to early morning classes $\textit{Assigned Early}_{icpt}$ is the instrumental variable in this study.

Although students are not all compliers of the early morning class treatment, over 85% 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:

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

$$Y_{icpt} = \alpha_0 + \alpha_1 Assigned\ Early_{icpt} + \alpha_2 S_i + Early\ Morning\ Probability\ Bin_{ict} + \sigma_{cpt} + \epsilon_{icpt} \quad (3)$$

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 (2).

In Table 5, I estimate the first-stage regression. The instrument is unsurprisingly strong with an F-statistics over 940 in each column.

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 6 by 2SLS and reduced form estimations of equation 2.[20] 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.[21]

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,

[20] I estimate the regression models by using only 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 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.

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

and indicators of requested class times in column 2, the estimates are still negative and 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 -0.0596 significant at the 5% level. In column 4, after replacing these course preference controls and course request fixed effects with simulated early morning section probability fixed effects, early morning classes lower GPA points by 0.0685 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).[22] Altogether, my results in Table 6 provide evidence that early morning classes reduce students' academic performance.[23]

These results establish that early-morning class assignments negatively impact students' final course grades. However, the extent of this effect may vary depending on whether students prefer early-morning or later sections. If students who voluntarily choose early classes perform better than those who are randomly assigned to them, it would suggest that preference plays a role in mitigating the adverse effects of early start times. Conversely, if students who prefer later classes experience a greater decline in performance when assigned to early sections, it would indicate that forced misalignment between preferred and actual schedules is particularly detrimental.

Table A.6 then explores the heterogeneity of these effects by incorporating interaction terms between 7:30 AM assignment and students' preferred section times. Column 2 presents results for students who preferred early-morning (7:30 AM) sections, while Column 3 focuses on students who preferred non-early-morning (Non-7:30 AM) sections. In column 2 of Panel

[22]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).

[23]In my sample, three mathematics courses—MA15800 (Precalculus: Functions and Trigonometry), MA16010 (Applied Calculus I), and MA16020 (Applied Calculus II)—have exams or overall grades that are standardized across all sections. I analyze the relationship between standardized course GPA and an indicator variable for whether students are assigned to an early morning (7:30 AM) section within these courses. The results suggest that attending early morning math classes reduces a student's standardized course GPA by 0.0265 standard deviations, although the estimated coefficient is not statistically significant.

A (Course Grades), it shows the interaction term for students who preferred early-morning classes is not statistically significant. However, students who preferred non-early-morning sections and were assigned a 7:30 AM class saw a positive and significant interaction effect in column 3.

Additionally, early-morning classes may influence students' performance in subsequent courses. To examine this, I analyze students' grades in sequential courses, which build directly on the content of a prior course. Table A.4 lists these courses with clear follow-up coursework. The results in Table A.7 show that while early-morning assignments may negatively affect immediate course performance, they do not have a statistically significant impact on students' grades in subsequent courses. Across 2SLS and reduced form estimates, the coefficients remain insignificant.

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 A.8 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.[24] The response rate was 0.409 with 343 respondents. Among the respondents, 0.51 of them were assigned to the 7:30 AM section, while 0.49 of

[24]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.

them got assigned to the later section.[25] The response rates of students who got assigned to both sections are balanced, so 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.[26] Then, I regressed the survey outcomes of interest on assigned early morning classes in the following model:

$$F_i = \delta_0 + \delta_1 Assigned\ Early_i + \delta_2 C_i + \tau_i + \varepsilon_i \tag{4}$$

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 7, 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 6 and A.8, which suggest that early morning classes lower academic performance.[27]

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 8, 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

[25]Figure 2 shows compliance comparisons among two sections.
[26]Please see Appendix II for the entire student survey and Appendix IV for the summary statistics.
[27]Table A.11 shows the consistent results for only freshman students.

I want to test if students actually performed better academically in the subsequent section. The results of Table 8 show no evidence that being assigned into subsequent classes may increase students' course grades.[28] Additionally, survey results from columns (1) to (4) of Panel 2 in Table 7 show no evidence about teaching quality in subsequent classes by same instructors. It is also possible that instructors, like students, may teach worse in early morning sections. If that is the case, I cannot completely rule out the influence of teaching quality as a channel.

One potential approach to disentangle the effects of teaching performance in early morning classes is to examine the impact of fatigue from "immediately preceding" or "back-to-back" classes on students' grades in subsequent courses proposed by Haggag *et al.* (2021). However, replicating this approach presents certain challenges in the context of Purdue University due to significant structural differences in scheduling compared to the United States Military Academy (USMA). [29]

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

[28] 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.

[29] At the USMA, a uniform class length, six potential start times, and four standardized time gaps between courses provide a consistent framework for defining "immediately preceding" or "back-to-back" classes. In contrast, Purdue University offers courses with varying lengths and as many as 40 potential starting times, leading to 76 distinct time gaps between classes (as detailed in Appendix Table A.12). This variability introduces challenges not only in defining the extensive margin (the number of preceding courses) but also in capturing the intensive margin (the cumulative fatigue or time investment from those courses). Differences in class duration, gaps between classes, and the possibility of students taking breaks further complicate efforts to apply the same identification strategy in a consistent and meaningful way across students. As a result, while this approach is well-suited to the more structured environment of the USMA, it is not directly applicable to the more sophisticated scheduling system at Purdue University.

morning class with the same specification in equation (3). I find no evidence that attending early morning classes affect academic performances in other courses in Table A.12.

6.2 The Effect on Educational Decisions

6.2.1 The Propensity to Take Additional Corresponding STEM Courses

In Table 9, I estimate equations (2) and (3) 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.[30] When I control for course request preferences 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 5.8 percentage points (or 22%) within the next two terms, an estimate that is statistically significant at the 1% level. When I include simulated early morning section probability fixed effects into the model, as shown in column 4, I find that students are less likely to take more STEM courses by 5.2 percentage points (or 20%) within the next two terms.[31] However, I do not see consistent heterogeneous effects on students' observable characteristics including gender, race, first generation status, and SAT scores.

These results strongly indicate that early-morning class assignments reduce students' likelihood of enrolling in additional STEM courses. However, the impact may vary depending on whether students preferred early or later sections, highlighting the role of preference

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

[31]I also explore the likelihood of students taking additional corresponding STEM courses in the very next first term alone in Table A.13. Estimated results are robust.

alignment in shaping academic outcomes.

In Table A.6, Panel B (STEM Courses) examines how these effects differ by students' section preferences. The interaction effect for students who preferred early-morning classes is statistically insignificant, indicating that their preference for early classes does not necessarily increase or decrease their likelihood of studying more STEM courses. In contrast, the negative impact on students who preferred later sections but were assigned to an early-morning class is particularly striking. Students were 26 percentage points less likely to enroll in a STEM course ($p < 0.01$). This substantial decline suggests that being forced into an early class, despite preferring a later schedule, may significantly discourage students from pursuing STEM pathways. These findings highlight that the misalignment between students' preferred and assigned class times can have severe academic consequences, particularly in fields that require sequential coursework and strong foundational skills like STEM.

My findings extend prior research on STEM persistence by highlighting how structural constraints, such as early class assignments, can discourage students from continuing in STEM. While Carrell *et al.* (2010) show that the shock of being assigned a female professor increases female students' likelihood of persisting in higher-level math courses by 34%, my results demonstrate that the shock of early morning class assignments leads to substantial declines in taking more STEM courses by 26%, regardless of demographic characteristics or academic ability.

6.2.2 The Propensity to Study a Major within the Same College

Table 10 discusses the propensity for students to study in a major within the same college corresponding to the assigned early morning classes. Similarly, I perform the 2SLS and the reduced form estimations of equations (2) and (3). I first regress an indicator for whether students study in a major within the same college by including the course-by-instructor fixed effect in column 1. I find that there are negative effects of attending early morning classes in column 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 major within the same college by 2.4 percentage points (or 23%) and 2.7 percentage points (or 25%). Furthermore, when I replace course request controls with simulated early-morning section probability fixed effects in column 4, the likelihood of choosing a major within the same college declines by 3.7 percentage points (or 35%), with greater precision and statistical significance at the 1% level.[32] In addition, I find that students who are assigned into early morning STEM classes are 3.8 percentage points (or 42%) less likely to study in a STEM major in column (2) of Table 11. On the other hand, I find no evidence from being enrolled in early morning non-STEM classes.

Overall, the results show that early-morning class assignments reduce the likelihood of majoring in the same college, especially in STEM. The effect is even stronger for students placed in early classes despite preferring later ones. In Table A.6, panel C (Major Choice) shows that students who preferred non-early-morning sections and were assigned an early morning class were 5.09 percentage points less likely to major in a subject from that class ($p < 0.10$), while the effect for students who preferred early-morning sections is negative but statistically insignificant. This suggests that misalignment between preferred and actual course timing may have long-term consequences for students' academic trajectories, particularly in major selection.

These findings highlight how structural barriers, such as early morning class assignments, can significantly reduce STEM persistence, aligning with prior research on major selection. Anelli *et al.* (2023) show that a 4.4 percentage point increase in the share of foreign-born peers in an introductory math course reduces the probability of domestic students graduating with a STEM degree by 4.7 percentage points. Similarly, my results suggest that early morning classes can have comparably large effects, reducing the likelihood of majoring in the STEM fields by 3.8 percentage points. Additionally, while Patterson *et al.* (2023) find that students are 1.4 percentage points (or 39%) more likely to graduate in a subject they were assigned

[32]In Table A.14, I further explore the heterogeneous effects of early morning classes on student's choice of major but find no evidence across students' demographic characteristics.

during the first semester of their sophomore year, my findings indicate that early morning class placement can have the opposite effect, decreasing the likelihood of majoring in the same college by 3.7 percentage points (or 35%).

6.2.3 The Likelihood of Graduating from a Low-Earning Major

I further examine the effect of early morning classes on students' likelihood to graduate from a low-earning major. The outcome variable of interest is an indicator of whether a student graduates from a low-earning major. I define majors with low earnings as college-major earnings in the first quartile ($Pr(Y_i \leq Q_{.25})$).

In column 1 of Table 12, I find that assignments to early morning classes increase the likelihood of graduating with a low-earning major by 5.5 percentage points (or 22%). The primary factor contributing to graduating from a low-earning major is enrollment in early morning STEM classes; as shown in column 2, attendance in these classes results in a 6.9 percentage point (or 24%) increase in the likelihood of selecting a low-earning major. Conversely, there is no evidence that students graduating from low-earning majors were influenced by enrollment in early morning non-STEM classes, as shown in column 3.

On the other hand, assignments to early-morning classes appear to crowd out students from middle-earning majors, as shown in columns 4 and 5. In column 4, being assigned to an early-morning class decreases the likelihood of graduating with a middle-earning major by 4.0 percentage points (or 16%), though the estimate lacks precision. Further disaggregating the results by STEM and non-STEM courses, I find that students placed in early-morning STEM classes are particularly affected, becoming less likely to graduate with a middle-earning major. This pattern suggests that these students may be shifting toward lower-earning majors, as indicated in columns 1 and 2. Results from columns 7 to 12 show no evidence that being assigned into early morning classes affects the probability to graduate from high-earning majors.[33]

[33]Table A.15 presents the effects of early morning classes on various outcomes for domestic students. The results are consistent with our main findings, showing estimates in the same direction; however, the estimates

Students assigned to early morning STEM courses are more likely to graduate with low-earning majors, in contrast to Anelli *et al.* (2023), who find that displaced students pivot to high-earning social science fields, avoiding wage penalties. Similarly, Bleemer (2022) shows that Proposition 209 lowered URM students' wages by 5%, while Bleemer & Mehta (2022) finds that missing the GPA cutoff for an economics major reduces early career wages by 46%. My results suggest that early morning class assignments can disrupt students' academic trajectories, increasing the probability for them to major in a low-earning majors by 5.5 percentage points (or 21%), and potentially leading to long-term financial consequences.

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 6 and A.8, there could be other mechanisms to my findings.

A potential mechanism underlying the negative effects on educational decisions could be attribution bias.[34] In my context, this refers to the possibility that students may misattribute the negative effect of early morning classes to their overall interest in the subject.

The survey responses suggest that attribution bias could be influencing students' views. As shown in Columns (5) and (6) of Panel 2 in Table 7, students reported lower enjoyment when attending early morning classes. However, it remains unclear whether this diminished enjoyment affected their stated willingness to take another course in the same subject.

An important alternative explanation for the lack of an effect on students' stated preferences could be related to how the survey prompted them to reflect on their course experience. As Haggag *et al.* (2019) suggest, asking students to consider whether they might have enjoyed the course more at a different time could have mitigated attribution bias by encouraging them to attribute their dissatisfaction to external factors, such as the class schedule, rather than to the course content. This could, in turn, influence how they perceived the course overall.

in columns 1 and 3 are imprecise.

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

Had the survey randomized the order of the questions, it would have been possible to test whether prompting students to reflect on these factors weakened attribution bias. Although this was not incorporated into the survey design, it is important to acknowledge that students' stated preferences for taking another course may still be influenced by this bias.

In Section 6.1, I discussed how STEM majors often impose minimum GPA or course grade thresholds, which may deter students with lower grades from continuing in STEM courses or selecting a related major. If this threshold effect is the primary driver, then attribution bias is not a necessary explanation, as the observed pattern would be a mechanical consequence of lower grades rather than an active decision by the student.

To examine this channel, I estimate the correlation between major choice and the course grades students received in their assigned early morning classes. It is important to acknowledge that the causal effect of grades on major choice differs from a simple observational relationship. However, the estimates in Table 13 indicate a weaker correlation between major selection and standardized course grades. Specifically, in column 2 of Table 13, a one standard deviation increase in grades is associated with a 3.8 percentage point increase in the likelihood of majoring in a STEM field. This implies that a 0.43 standard deviation decrease in grades corresponds to a 43% reduction in the probability of majoring in STEM, shown in Table 11. This effect is larger than the estimates reported in Haggag *et al.* (2021), suggesting that the relationship between academic performance and major selection may be more pronounced in this context.[35]

7 Discussion and Conclusion

This study provides strong evidence that early morning class assignments negatively impact students' academic performance and long-term educational trajectories. Leveraging a natural experiment at a large public university, I find that students assigned to early morning classes

[35]Main & Ost (2014) find that letter grades in economics have no significant effect on students' enrollment in the major.

earn lower grades, are less likely to continue in STEM courses, are less inclined to major in the same discipline as their early morning course, and are more likely to graduate with a lower-earning major. These effects are particularly pronounced in STEM courses, suggesting that rigid scheduling policies may unintentionally discourage students from pursuing STEM fields.

Given these findings, university administrators should reconsider course scheduling practices, particularly for gateway STEM courses, which serve as critical entry points into high-earning degrees in science and technology. Scheduling these courses during periods of peak cognitive alertness could improve STEM persistence and long-term labor market outcomes. At the same time, universities can implement meaningful scheduling adjustments without significant financial investment. By prioritizing later morning or early afternoon slots for high-impact STEM courses while reserving early morning periods for subjects less affected by cognitive fatigue, institutions can enhance student success at minimal cost. Additionally, integrating sleep science education into orientation programs and training faculty on best practices for early morning instruction are practical, low-cost interventions that align scheduling policies with students' biological rhythms, optimizing both learning and retention outcomes.

Furthermore, evidence of attribution bias suggests that students may mistakenly attribute their struggles in early morning courses to a lack of ability or interest rather than recognizing the role of sleep deprivation. To counteract this misattribution, universities should enhance transparency regarding the impact of class timing on performance. Academic advisors and course registration platforms could incorporate alerts or recommendations, particularly for first-year students, to help them make informed scheduling decisions. To support students navigating early morning courses, universities could offer flexible learning options, such as recorded lectures or hybrid attendance models, allowing students to engage with material during their peak cognitive hours. Additionally, instructors teaching early morning STEM courses could adopt active learning strategies—such as interactive problem-solving and col-

laborative exercises—to improve engagement and mitigate the effects of morning fatigue. Beyond scheduling adjustments, policymakers and higher education institutions could consider broader structural reforms, such as delaying university start times to better align with research on adolescent circadian rhythms. While such changes may pose logistical challenges, including classroom availability and faculty scheduling, the potential benefits in student retention, STEM persistence, and long-term labor market readiness make it a worthwhile consideration.

Finally, future research should examine whether targeted interventions—such as flexible attendance policies, hybrid learning models, or sleep education initiatives—can further mitigate the negative effects of early morning classes. Given the economic significance of STEM fields and the long-term financial impact of major selection, even minor scheduling adjustments could yield substantial benefits for students and society alike.

8 Figures and Tables

Figure 1: Hypothetical Course Registration Timeline

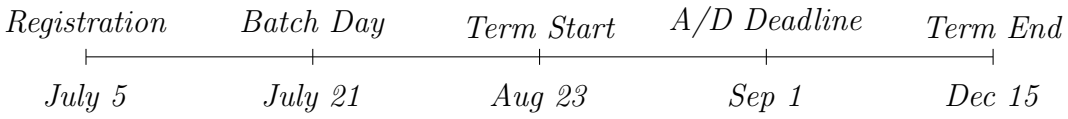


Figure 2: Class Compliance Comparisons in Econ 25200



Table 1: Summary Statistics - Sample Comparison

	All Freshmen	Freshmen in Batch	Freshmen in Batched (Specific)	Main Sample
Female	0.451	0.478	0.477	0.565
	(0.498)	(0.500)	(0.499)	(0.496)
White	0.621	0.651	0.655	0.732
	(0.485)	(0.477)	(0.481)	(0.443)
Black	0.0328	0.0283	0.0260	0.0465
	(0.178)	(0.166)	(0.168)	(0.210)
Hispanic	0.0605	0.0599	0.0605	0.0606
	(0.238)	(0.237)	(0.245)	(0.239)
Asian	0.0964	0.0928	0.0940	0.140
	(0.295)	(0.290)	(0.278)	(0.347)
Other	0.05851	0.0595	0.0589	0.0203
	(0.235)	(0.237)	(0.233)	(0.141)
1st Gen Student	0.118	0.116	0.117	0.184
	(0.322)	(0.320)	(0.331)	(0.387)
SAT Combined	1,283.49	1,282.96	1,283.631	1,249.25
	(149.56)	(145.69)	(138.31)	(122.56)
Citizen	0.869	0.892	0.894	0.839
	(0.337)	(0.311)	(0.336)	(0.367)
Requested Course		13.993	14.005	13.118
		(4.440)	(4.432)	(3.483)
N	71,435	52,250	50,196	9,020

Notes: Column 1 presents a sample of 71,435 student-by-course-by-term observations for all freshmen in Fall 2018 and Fall 2019. Column 2 shows a subset of 52,250 observations for freshmen enrolled through the batch registration system during the same terms. Column 3 includes 50,196 observations from these cohorts, specifically focusing on non-athlete students taking lower-level courses and aged between 18 and 21. Column 4 represents the primary analysis sample, consisting of 9,020 student-by-course-by-term observations. Columns 1 and 2 of Table 2 correspond to the split samples of Column 4 in Table 1. Standard deviations are reported in parentheses.

Table 2: Summary Statistics - Student Demographics

	Main Sample		Subsample - STEM Courses		Subsample - Major	
	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	1,238.911	1,251.904	1,235.11	1,243.92	1,243.53	1,262.00
	(120.613)	(122.92)	(118.959)	(116.189)	(123.432)	(130.600)
Citizen	0.848	0.837	0.860	0.858	0.831	0.811
	(0.129)	(0.136)	(0.348)	(0.349)	(0.375)	(0.392)
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 left panel displays the main sample of 9,020 student-by-course-by-term observations. The middle panel displays a subsample of 5,118 student-by-course-by-term observations from Fall 2018 and Fall 2019. This subsample is restricted to non-athlete freshman students between the ages of 18 and 21 years old, drawn from the larger main sample. The right panel displays a subsample of 3,912 student-by-course observations from the Fall 2018 cohort within the main sample. Standard deviation is in parentheses.

Table 3: Summary Statistics - Outcome Variables

	Assigned Early (1)	Assigned Non-Early (2)
Course GPA	2.97	3.01
	(1.033)	(0.994)
Observations	1,846	7,174
STEM Courses	0.276	0.256
	(0.447)	(0.436)
Observations	1,090	4,028
Major Choice	0.130	0.098
	(0.337)	(0.297)
Observations	759	3,153
Major Earnings	49,973	52,161
	(11,792)	(12,388)
Observations	750	3,106

Notes: The observations are in student-by-course-by-term level. Standard deviation is in parentheses.

Table 4: Student-by-Course-by-Term Level Balance Test

	(1)	(2)	(3)	(4)
Female	0.047*	0.006	0.006	0.003
	(0.027)	(0.007)	(0.007)	(0.006)
Black	-0.019	-0.005	-0.006	-0.005
	(0.018)	(0.015)	(0.015)	(0.013)
Hispanic	-0.000	0.000	0.003	0.014*
	(0.015)	(0.009)	(0.009)	(0.007)
Asian	-0.024	-0.011	-0.011	-0.009
	(0.015)	(0.010)	(0.010)	(0.007)
Other Race/Ethnicity	-0.020	-0.004	-0.002	-0.002
	(0.026)	(0.019)	(0.020)	(0.015)
First Generation	-0.009	-0.008	-0.007	-0.004
	(0.014)	(0.008)	(0.008)	(0.006)
Citizen	-0.015	0.004	0.004	0.004
	(0.013)	(0.005)	(0.005)	(0.004)
Standardized SAT Combined	-0.015	-0.005	-0.005	-0.002
	(0.010)	(0.005)	(0.004)	(0.004)
F-stat P-Value	0.351	0.382	0.412	0.539
Observations	9,020	9,020	9,020	9,020
R^2	0.008	0.363	0.365	0.499
Course-Instructor-Term FE	N	Y	Y	Y
Course Preference Controls	N	Y	Y	N
Number of Courses Requested FE	N	N	Y	N
Simulated 7:30 AM Section Probability FE	N	N	N	Y

Notes: Robust standard errors in parentheses are clustered at the individual and course-by-term levels (6,202 clusters at the individual level and 563 clusters for section-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 non-athlete freshman cohort between the age of 18 and 21 from Fall 2018 and Fall 2019. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: First Stage Estimates

	(1)	(2)	(3)	(4)
Assigned 7:30 AM Section	0.853***	0.850***	0.850***	0.857***
	(0.0275)	(0.0277)	(0.0277)	(0.0265)
Course-Instructor-Term FE	Y	Y	Y	Y
Course Request Controls	N	Y	Y	N
Demographic Controls	N	N	Y	Y
Simulated 7:30 AM Section Probability FE	N	N	N	Y
F-Statistics	964.645	941.000	944.385	1,042.735
N	9,020	9,020	9,020	9,020
R^2	0.881	0.882	0.882	0.882

Notes: This table shows the first stage estimates. The observations are non-athlete freshman cohort between the age of 18 and 21 from Fall 2018 and Fall 2019 who were assigned to lower-level (100 or 200 level) classes either in an early morning (7:30 AM) section or a non-early morning section. There are 60 course-by-instructor-by-semester fixed effect in this specification. All observations are accounted for within these fixed effects. Robust standard errors in parentheses are clustered at the individual and section-by-term levels (5,029 clusters at the individual level and 313 clusters for section-by-term level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Effect on Course Grades

	Panel 1: 2SLS Estimates			
	(1)	(2)	(3)	(4)
Assigned 7:30 AM Section	-0.0806	-0.0559	-0.0596**	-0.0685**
	(0.0518)	(0.0420)	(0.0269)	(0.0307)
Course-Instructor-Term FE	Y	Y	Y	Y
Course Request Controls	N	Y	Y	N
Demographic Controls	N	N	Y	Y
Simulated 7:30 AM Section Probability FE	N	N	N	Y
N	9,020	9,020	9,020	9,020
Dependent Variable Mean	3.00	3.00	3.00	3.00
	Panel 2: Reduced Form Estimates			
	(1)	(2)	(3)	(4)
Assigned 7:30 AM Section	-0.0687	-0.0475	-0.0507**	-0.0586**
	(0.0438)	(0.0353)	(0.0227)	(0.0257)
Course-Instructor-Term FE	Y	Y	Y	Y
Course Request Controls	N	Y	Y	N
Demographic Controls	N	N	Y	Y
Simulated 7:30 AM Section Probability FE	N	N	N	Y
N	9,020	9,020	9,020	9,020
R^2	0.119	0.130	0.240	0.232
Dependent Variable Mean	3.00	3.00	3.00	3.00

Notes: Observations are non-athlete freshman students between the age of 18 and 21 from Fall 2018 and Fall 2019. There are 60 course-by-instructor-by-semester fixed effect in this specification. All observations are accounted for within these fixed effects. Robust standard errors in parentheses are clustered at the individual and course-by-term levels (5,029 clusters at the individual level and 313 clusters for section-by-term level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: 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 8: 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	0.0179	0.00358	0.00120	0.00567
	(0.0386)	(0.0175)	(0.0201)	(0.0102)
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	37,749	37,749	37,749	37,749
R^2	0.264	0.209	0.304	0.118
Dependent Variable Mean	3.22	0.774	0.516	0.0801

Notes: Observations are from 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 and Fall 2019. 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 9: Effect on STEM Courses within the Next 2 Terms

	Panel 1: 2SLS Estimates			
	(1)	(2)	(3)	(4)
Assigned 7:30 AM Section	-0.0471**	-0.0569***	-0.0582***	-0.0519***
	(0.0218)	(0.0203)	(0.0199)	(0.0191)
Course-Instructor-Term FE	Y	Y	Y	Y
Course Request Controls	N	Y	Y	N
Demographic Controls	N	N	Y	Y
Simulated 7:30 AM Section Probability FE	N	N	N	Y
N	5,118	5,118	5,118	5,118
Dependent Variable Mean	0.260	0.260	0.260	0.260
	Panel 2: Reduced Form Estimates			
	(1)	(2)	(3)	(4)
Assigned 7:30 AM Section	-0.0402**	-0.0484***	-0.0527***	-0.0447***
	(0.0189)	(0.0178)	(0.0170)	(0.0169)
Course-Instructor-Term FE	Y	Y	Y	Y
Course Request Controls	N	Y	Y	N
Demographic Controls	N	N	Y	Y
Simulated 7:30 AM Section Probability FE	N	N	N	Y
N	5,118	5,118	5,118	5,118
R^2	0.070	0.093	0.089	0.072
Dependent Variable Mean	0.260	0.260	0.260	0.260

Notes: Observations are non-athlete freshman cohort between the age of 18 and 21 from Fall 2018 and Fall 2019. There are 38 course-by-instructor-by-semester fixed effect in this specification. All observations are accounted for within these fixed effects. 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: Effect on Choice of Major (College Level)

	Panel 1: 2SLS Estimates			
	(1)	(2)	(3)	(4)
Assigned 7:30 AM Section	-0.0234*	-0.0239*	-0.0265*	-0.0367***
	(0.0129)	(0.0141)	(0.0141)	(0.0141)
Course-Instructor-Term FE	Y	Y	Y	Y
Course Request Controls	N	Y	Y	N
Demographic Controls	N	N	Y	Y
Simulated 7:30 AM Section Probability FE	N	N	N	Y
N	3,912	3,912	3,912	3,912
Dependent Variable Mean	0.104	0.104	0.104	0.104
	Panel 2: Reduced Form Estimates			
	(1)	(2)	(3)	(4)
Assigned 7:30 AM Section	-0.0207*	-0.0210*	-0.0212*	-0.0323***
	(0.0112)	(0.0122)	(0.0122)	(0.0116)
Course-Instructor-Term FE	Y	Y	Y	Y
Course Request Controls	N	Y	Y	N
Demographic Controls	N	N	Y	Y
Simulated 7:30 AM Section Probability FE	N	N	N	Y
N	3,912	3,912	3,912	3,912
R^2	0.198	0.209	0.226	0.215
Dependent Variable Mean	0.104	0.104	0.104	0.104

Notes: Observations are non-athlete freshman cohort between the age of 18 and 21 from Fall 2018. There are 39 course-by-instructor fixed effect in this specification. All observations are accounted for within these fixed effects. 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 11: Effect on Choice of STEM Major (College Level)

	Overall	STEM	Non-STEM
	(1)	(2)	(3)
Assigned 7:30 AM Section	-0.0323***	-0.0377***	0.0142
	(0.0116)	(0.0109)	(0.0965)
Course-Instructor FE	Y	Y	Y
Demographic Controls	Y	Y	Y
Simulated 7:30 AM Section Probability FE	Y	Y	Y
N	3,912	2,555	1,357
R^2	0.215	0.255	0.185
Dependent Variable Mean	0.104	0.0881	0.135

Notes: Observations are non-athlete freshman cohort between the age of 18 and 21 from Fall 2018. There are 39 course-by-instructor fixed effect in this specification. All observations are accounted for within these fixed effects. 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 12: Effect on Major Earnings

	$\Pr(Y_i \leq Q_{.25})$			$\Pr(Q_{.25} \leq Y_i \leq Q_{.5})$			$\Pr(Q_{.5} \leq Y_i \leq Q_{.75})$			$\Pr(Q_{.75} \leq Y_i \leq Q_1)$		
	Combined (1)	STEM (2)	Non-STEM (3)	Combined (4)	STEM (5)	Non-STEM (6)	Combined (7)	STEM (8)	Non-STEM (9)	Combined (10)	STEM (11)	Non-STEM (12)
Assigned 7:30 AM Section	0.0552**	0.0689***	-0.0600	-0.0398	-0.0536*	0.0953	-0.0168	-0.00912	-0.0526	0.00146	-0.00624	0.0173
	(0.0257)	(0.0258)	(0.0724)	(0.0327)	(0.0318)	(0.0766)	(0.0371)	(0.0380)	(0.0668)	(0.0136)	(0.0123)	(0.0420)
Course-Instructor-Term FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Simulated 7:30 AM Section Probability FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	3,856	2,513	1,343	3,856	2,513	1,343	3,856	2,513	1,343	3,856	2,513	1,343
R^2	0.148	0.119	0.213	0.124	0.104	0.199	0.122	0.133	0.132	0.326	0.258	0.419
Dependent Variable Mean	0.255	0.281	0.208	0.253	0.281	0.201	0.246	0.261	0.218	0.246	0.178	0.373

Notes: Observations are non-athlete freshman cohort between the age of 18 and 21 from Fall 2018. There are 39 course-by-instructor fixed effect in this specification. All observations are accounted for within these fixed effects. $\Pr(Y_i \leq Q_{.25})$ refers to the college-major earnings that fall into the 1st quartile 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. $\Pr(Q_{.25} \leq Y_i \leq Q_{.5})$ represents the college-major earnings within the 25th to 50th percentile range of the major-earnings distribution. In columns (4), (5), and (6), the outcome variable is an indicator for whether students graduated from a college major within the 25th-to-50th earnings range. $\Pr(Q_{.5} \leq Y_i \leq Q_{.75})$ represents the college-major earnings within the 50th to 75th percentile range of the major-earnings distribution. In columns (7), (8), and (9), the outcome variable is an indicator for whether students graduated from a college major within the 50th-to-75th earnings range. $\Pr(Q_{.75} \leq Y_i \leq Q_{.1})$ represents the college-major earnings within the 75th to 100th percentile range of the major-earnings distribution. In columns (10), (11), and (12), the outcome variable is an indicator for whether students graduated from a college major within the 75th-to-100th earnings range. Robust standard errors in parentheses are clustered at the individual and section levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Correlation between Major Choice and Standardized Course Grades

	Overall	STEM	Non-STEM
	(1)	(2)	(3)
Standardized Course Grades	0.0104*	0.0236***	-0.0527***
	(0.00577)	(0.00582)	(0.0193)
Course-Instructor FE	Y	Y	Y
Demographic Controls	Y	Y	Y
Simulated 7:30 AM Section Probability FE	Y	Y	Y
N	3,910	2,553	1,357
R^2	0.207	0.249	0.160

Notes: Observations are non-athlete freshman cohort between the age of 18 and 21 from Fall 2018. Two students did not complete the course and were not assigned grades. There are 39 course-by-instructor fixed effect in this specification. There are 39 course-by-instructor fixed effect in this specification. All observations are accounted for within these fixed effects. Robust standard errors in parentheses are clustered at the individual and section levels (2,811, 1,994, and 1,293 clusters at the individual level and 237, 90, and 147 clusters for section level in columns 1, 2, and 3 respectively). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Appendix I Batch Registration

Purdue University employs a specialized course registration algorithm, as described in Mumford *et al.* (2024) and developed by Müller & Murray (2010), to assign undergraduate courses. This algorithm processes students' ranked course preferences to construct schedules for the entire student population. Its primary objective is to prioritize students' top course choices while reducing dependence on alternative selections. The algorithm assigns a weight to each request using the following formula:

$$weight(a \in dom(R)) = 0.9^{prior(R)} \times 0.5^{alt(a)}, \tag{5}$$

where *prior(R)* denotes the ranking position of a course request, and *alt(a)* indicates whether alternative course options were provided. For instance, as shown in Figure A.1, a first-choice course with no listed alternatives receives a weight of 0.9, while second and third choices are weighted progressively lower. The algorithm determines course assignments using Iterative Forward Search (Müller & Murray, 2010), applying stricter penalties for rejecting requests that list no alternative courses compared to those that do.

The course allocation process adheres to four primary constraints:

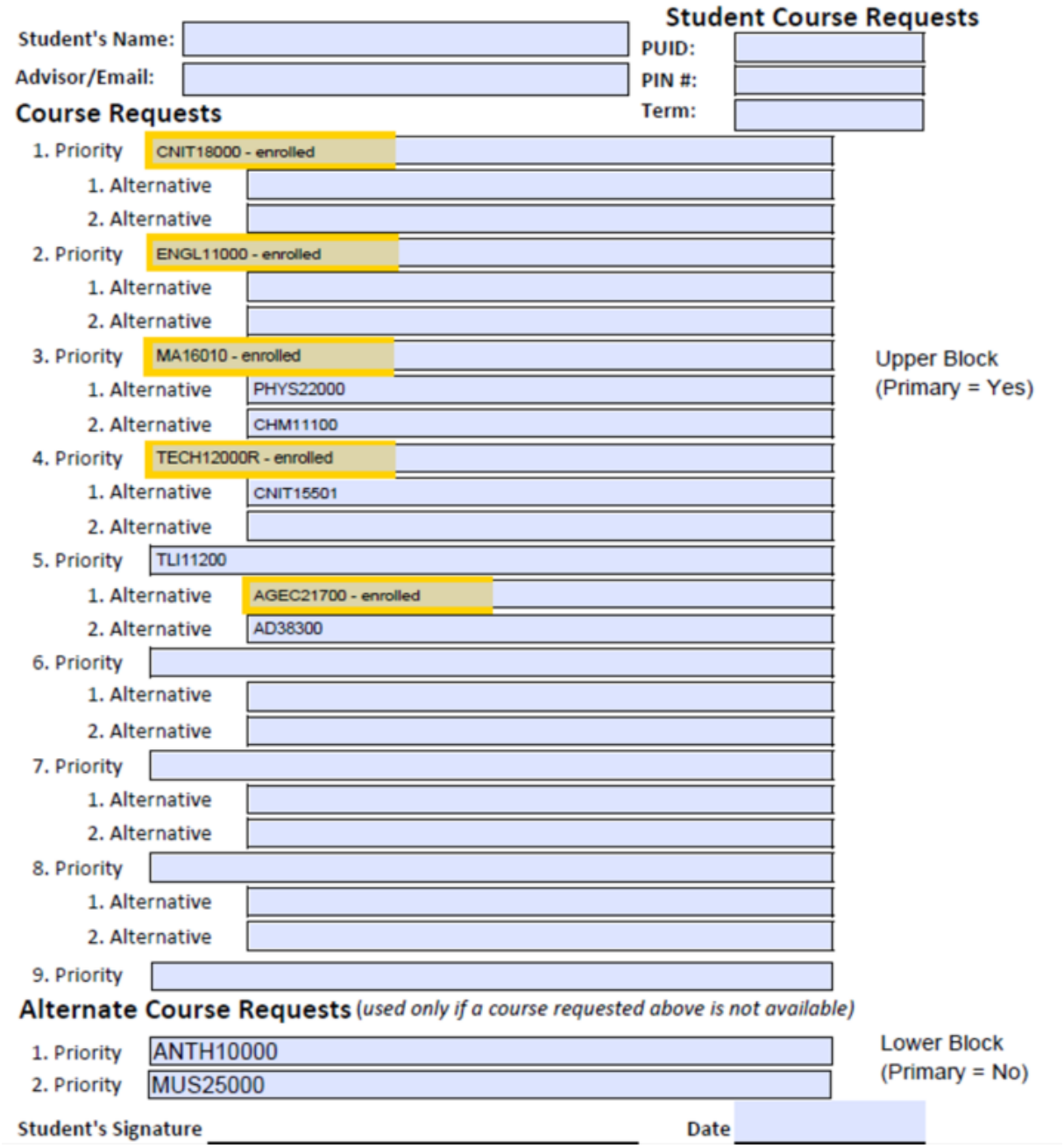
1. **Seat Availability:** Each course section has a fixed capacity, though some, such as online courses, may have no enrollment limit.

2. **Schedule Conflicts:** Students cannot be enrolled in courses that have overlapping time slots.

3. **Geographic Constraints:** If two sections are scheduled in locations that require significant travel time, the algorithm avoids scheduling them back-to-back unless they are at least 20 minutes apart.

4. **Major-Specific Enrollment:** Some courses reserve seats exclusively for students within particular majors.

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 [anonymized names], a Purdue PhD student in economics. Dr. [anonymized name] 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. [anonymized name] 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 [anonymized name] (anonymized email address) if you have further

questions.

Best wishes,

[anonymize

d name]

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

Powered by Qualtrics

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, I test the strength of the instrument by estimating the first-stage regression with the following equation:

$$Finalized\ Early_{icpt} = \beta_0 + \gamma Assigned\ Early_{icpt} + \beta_1 S_i + \beta_2 C_{ict} + \sigma_{cpt} + \varepsilon_{icpt} \tag{6}$$

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: Student-by-Course-by-Term Level Balance Test (Alternative Specifications)

	(1)	(2)	(3)	(4)
Female	0.047**	0.006	0.006	0.003
	(0.019)	(0.008)	(0.008)	(0.007)
Black	-0.019	-0.005	-0.006	-0.005
	(0.022)	(0.018)	(0.018)	(0.015)
Hispanic	-0.000	0.000	0.003	0.014**
	(0.012)	(0.007)	(0.007)	(0.006)
Asian	-0.024*	-0.011	-0.011	-0.009
	(0.013)	(0.009)	(0.009)	(0.007)
Other Race/Ethnicity	-0.020	-0.004	-0.002	-0.002
	(0.026)	(0.024)	(0.025)	(0.021)
First Generation	-0.009	-0.008	-0.007	-0.004
	(0.014)	(0.009)	(0.009)	(0.007)
Citizen	-0.015	0.004	0.004	0.004
	(0.014)	(0.004)	(0.005)	(0.004)
Standardized SAT Combined	-0.015	-0.005	-0.005	-0.002
	(0.009)	(0.005)	(0.004)	(0.005)
F-stat P-Value	0.22	0.105	0.14	0.37
Observations	9,020	9,020	9,020	9,020
R^2	0.008	0.363	0.365	0.499
Course-Instructor-Term FE	N	Y	Y	Y
Course Preference Controls	N	Y	Y	N
Number of Courses Requested FE	N	N	Y	N
Simulated 7:30 AM Section Probability FE	N	N	N	Y

Notes: Robust standard errors in parentheses are clustered at the individual and course-by-term levels (6,204 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 4. Observations are 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.2: Courses in the Three Samples

Main Sample			Subsample - STEM Courses			Subsample - Major		
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	1886	562	Fundamentals Of Biology I	1,325	383	Fundamentals Of Biology I	563	179
Principles Of Biology	6	2	Principles Of Biology	6	2	Human Anatomy and Physiology	256	125
Human Anatomy And Physiology	759	326	Human Anatomy And Physiology	503	201	Fundamentals Of Speech Communication	601	65
Fundamentals Of Speech Communication	602	65	Macroeconomics	77	76	Macroeconomics	75	72
Macroeconomics	152	148	Functions And Trigonometry	928	113	Exploring Teaching As A Career	42	17
Exploring Teaching As A Career	42	17	Applied Calculus I	2,032	161	Multiculturalism And Education	29	8
Multiculturalism And Education	29	8	Applied Calculus II	64	15	First-Year Composition	492	25
First-Year Composition	491	25	Statistics And Society	138	106	French Level III	8	2
French Level III	8	2				Functions And Trigonometry	424	47
Functions And Trigonometry	1,347	158				Applied Calculus I	1,009	71
Applied Calculus I	3,039	232				Applied Calculus II	58	14
Applied Calculus II	122	29				Spanish Level III	160	5
Spanish Level III	160	5				Spanish Level IV	25	5
Spanish Level IV	25	5				Statistics And Society	132	97
Statistics And Society	270	203						

Table A.3: Mapping Between Courses and Colleges

Course Title	College	Fraction
Macroeconomics	Business	0.453
Exploring Teaching	Education	0.48
Multiculturalism & Education	Education	0.66
Fundamentals of Speech	Liberal Arts	0.11
English Composition	Liberal Arts	0.10
French Level III	Liberal Arts	0.13
Spanish Level III	Liberal Arts	0.16
Spanish Level IV	Liberal Arts	0.32
Basic Aircraft Science	Polytechnic Institute	0.947
Biology I	Science	0.039
Human Anatomy And Physiology	Science	0.0078
Precalculus	Science	0.050
Applied Calculus I	Science	0.099
Applied Calculus II	Science	0.172
Statistics & Society	Science	0.0076

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.4: List of Courses with Direct Follow-Up Courses in the Study

Initial Course	**Follow-Up Course(s)**
Fundamentals of Biology I	Fundamentals of Biology II
Macroeconomics	Intermediate Macroeconomics
French Level III	French Level IV
Precalculus	Plane Analytic Geometry and Calculus I
	Applied Calculus I
	Analytic Geometry and Calculus I
Applied Calculus I	Applied Calculus II
	Plane Analytic Geometry and Calculus II
	Analytic Geometry and Calculus II
Plane Analytic Geometry and Calculus II	Multivariate Calculus
Spanish Level III	Spanish Level IV
Spanish Level IV	Spanish Level V

Table A.5: Effect on Standardized Course Grades

	Panel 1: 2SLS Estimates			
	(1)	(2)	(3)	(4)
Assigned 7:30 AM Section	-0.0804	-0.0557	-0.0595**	-0.0684**
	(0.0510)	(0.0413)	(0.0269)	(0.0306)
Course-Instructor-Term FE	Y	Y	Y	Y
Course Request Controls	N	Y	Y	Y
Demographic Controls	N	N	Y	Y
Simulated 7:30 AM Section Probability FE	N	N	N	Y
N	9,020	9,020	9,020	9,020
	Panel 2: OLS Estimates			
	(1)	(2)	(3)	(4)
Assigned 7:30 AM Section	-0.0685	-0.0517	-0.0532**	-0.0585**
	(0.0437)	(0.0359)	(0.0231)	(0.0257)
Course-Instructor-Term FE	Y	Y	Y	Y
Course Request Controls	N	Y	Y	Y
Demographic Controls	N	N	Y	Y
Simulated 7:30 AM Section Probability FE	N	N	N	Y
N	9,020	9,020	9,020	9,020
R^2	00.119	0.123	0.235	0.232

Notes: Observations are non-athlete freshman cohort between the age of 18 and 21 from Fall 2018 and Fall 2019. 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.6: Heterogeneous Effects of Preferred Sections on Student Outcomes

	(1)	(2)	(3)
Panel A: Course Grades			
Assigned 7:30 AM	-0.0586**	-0.0563**	-0.0610**
	(0.0257)	(0.0250)	(0.0251)
Assigned 7:30 AM × Preferred 7:30 AM		-0.487	
		(0.713)	
Assigned 7:30 AM × Preferred Non-7:30 AM			0.509**
			(0.241)
N	9,020	9,020	9,020
R^2	0.232	0.232	0.232
Panel B: STEM Courses			
Assigned 7:30 AM	-0.0447***	-0.0446***	-0.0439***
	(0.0169)	(0.0171)	(0.0167)
Assigned 7:30 AM × Preferred 7:30 AM		-0.00805	
		(0.112)	
Assigned 7:30 AM × Preferred Non-7:30 AM			-0.262***
			(0.0425)
N	5,118	5,118	5,118
R^2	0.077	0.077	0.078
Panel C: Major Choice			
Assigned 7:30 AM	-0.0323***	-0.0318***	-0.0320***
	(0.0116)	(0.0115)	(0.0116)
Assigned 7:30 AM × Preferred 7:30 AM		-0.0905	
		(0.0781)	
Assigned 7:30 AM × Preferred Non-7:30 AM			-0.0509***
			(0.0117)
N	3,912	3,912	3,912
R^2	0.215	0.215	0.215

Notes: Observations are non-athlete freshman cohort between the age of 18 and 21 from Fall 2018 and Fall 2019. Column 1 presents the benchmark specification without interaction terms for preferred sections. Column 2 includes an interaction term for students who preferred early-morning sections, while Column 3 includes an interaction term for students who preferred non-early-morning sections. All columns in Panels A, B, and C include course-by-instructor-by-term fixed effects, simulated 7:30 am section probability fixed effects,and demographic controls. Robust standard errors in parentheses are clustered at the individual and section-by-term levels. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.7: Effect on Sequential Course Grades

	Panel 1: 2SLS Estimates			
	(1)	(2)	(3)	(4)
Assigned 7:30 AM Section	0.0443	0.0215	0.0266	0.0384
	(0.0513)	(0.0386)	(0.0446)	(0.0426)
Course-Instructor-Term FE	Y	Y	Y	Y
Course Request Controls	N	Y	Y	N
Demographic Controls	N	N	Y	Y
Simulated 7:30 AM Section Probability FE	N	N	N	Y
N	3,626	3,626	3,626	3,626
Dependent Variable Mean	2.98	2.98	2.98	2.98
	Panel 2: Reduced Form Estimates			
	(1)	(2)	(3)	(4)
Assigned 7:30 AM Section	0.0383	-0.0185	0.0230	0.0332
	(0.0445)	(0.0337)	(0.0389)	(0.0367)
Course-Instructor-Term FE	Y	Y	Y	Y
Course Request Controls	N	Y	Y	N
Demographic Controls	N	N	Y	Y
Simulated 7:30 AM Section Probability FE	N	N	N	Y
N	3,626	3,626	3,626	3,626
R^2	0.270	0.290	0.336	0.325
Dependent Variable Mean	2.98	2.98	2.98	2.98

Notes: Observations are non-athlete freshman students between the age of 18 and 21 from Fall 2018 and Fall 2019. All observations are accounted for within these fixed effects. Robust standard errors in parentheses are clustered at the individual and course-by-term levels (2,142 clusters at the individual level and 171 clusters for section-by-term level). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: 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	-0.00634	-0.0146	-0.0213*	-0.0291**	-0.0285**	-0.0244**	-0.0244**	-0.0129	-0.00797	-0.00662	-0.00753
	(0.0119)	(0.0125)	(0.0116)	(0.0121)	(0.0117)	(0.0122)	(0.0122)	(0.0112)	(0.00978)	(0.00595)	(0.00594)
Course-Instructor-Term FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Simulated 7:30 AM Section Probability FE	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	0.189	0.196	0.213	0.187	0.172	0.166	0.166	0.096	0.093	0.052	0.046
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 non-athlete freshman students between the age of 18 and 21 from Fall 2018 and Fall 2019. There are 78 instructors who teach an early-morning course and also teach multiple sections of the same course in the same semester. Observations are 606 less than the observations in Table 4 because this sample does not include students who withdrew those courses or audited those courses. Hence, final course grades are not available for those students. 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.9: 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 7. Standard deviation is in parentheses.

Table A.10: 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.11: 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.12: Effect on Leave-One-Out Term GPA

	Panel 1: 2SLS Estimates			
	(1)	(2)	(3)	(4)
Assigned 7:30 AM Section	0.0135	0.0276	0.0215	0.0107
	(0.0383)	(0.0332)	(0.0289)	(0.0323)
Course-Instructor-Term FE	Y	Y	Y	Y
Course Request Controls	N	Y	Y	N
Demographic Controls	N	N	Y	N
Simulated 7:30 AM Section Probability FE	N	N	N	Y
N	8,981	8,981	8,981	8,981
Dependent Variable Mean	3.21	3.21	3.21	3.21
	Panel 2: Reduced Form Estimates			
	(1)	(2)	(3)	(4)
Assigned 7:30 AM Section	0.0115	0.0235	0.0182	0.00913
	(0.0330)	(0.0286)	(0.0250)	(0.0280)
Course-Instructor-Term FE	Y	Y	Y	Y
Course Request Controls	N	Y	Y	N
Demographic Controls	N	N	Y	N
Simulated 7:30 AM Section Probability FE	N	N	N	Y
N	8,981	8,981	8,981	8,981
R^2	0.057	0.072	0.147	0.135
Dependent Variable Mean	3.21	3.21	3.21	3.21

Notes: Observations are non-athlete freshman students between the age of 18 and 21 from Fall 2018 and Fall 2019. The number of observation is 8,981 that is lower than the number of observation (9,020) in Table A.8 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 A.13: Effect on Corresponding STEM Courses in the Next Term

	Panel 1: 2SLS Estimates			
	(1)	(2)	(3)	(4)
Assigned 7:30 AM Section	-0.0310	-0.0399*	-0.0411**	-0.0333
	(0.0212)	(0.0206)	(0.0202)	(0.0206)
Course-Instructor-Term FE	Y	Y	Y	Y
Course Request Controls	N	Y	Y	N
Demographic Controls	N	N	Y	N
Simulated 7:30 AM Section Probability FE	N	N	N	Y
N	5,118	5,118	5,118	5,118
Dependent Variable Mean	0.205	0.205	0.205	0.205
	Panel 2: Reduced Form Estimates			
	(1)	(2)	(3)	(4)
Assigned 7:30 AM Section	-0.0265	-0.0354**	-0.0350*	-0.0287
	(0.0184)	(0.0177)	(0.0176)	(0.0180)
Course-Instructor-Term FE	Y	Y	Y	Y
Course Request Controls	N	Y	Y	N
Demographic Controls	N	N	Y	N
Simulated 7:30 AM Section Probability FE	N	N	N	Y
N	5,118	5,118	5,118	5,118
R^2	0.044	0.055	0.057	0.048
Dependent Variable Mean	0.205	0.205	0.205	0.205

Notes: Observations are non-athlete freshman cohort between the age of 18 and 21 from Fall 2018 and Fall 2019 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.14: Heterogeneous Effect on Choice of Major (College Level)

	(1)	(2)	(3)	(4)	(5)
Assigned 7:30 AM Section	-0.0323***	-0.0673*	-0.0326**	-0.0338**	-0.0231*
	(0.0116)	(0.0392)	(0.0134)	(0.0132)	(0.0134)
Female × Assigned 7:30 AM Section		0.0510			
		(0.0519)			
Black × Assigned 7:30 AM Section			-0.0433		
			(0.0381)		
Hispanic × Assigned 7:30 AM Section			-0.0462		
			(0.0594)		
Asian × Assigned 7:30 AM Section			0.0216		
			(0.0395)		
Other × Assigned 7:30 AM Section			0.0536		
			(0.0811)		
Standardized SAT × Assigned 7:30 AM Section				-0.00693	
				(0.0210)	
1st Gen Student × Assigned 7:30 AM Section					-0.0494
					(0.0315)
Course-Instructor FE	Y	Y	Y	Y	Y
Simulated 7:30 AM Section Probability FE	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	0.215	0.216	0.216	0.216	0.216
Dependent Variable Mean	0.104	0.104	0.104	0.104	0.104

Notes: Observations are 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 A.15: Effects on Different Outcomes for Domestic Students

	Course GPA (1)	STEM Courses (2)	Major Choice (3)	Q1 Major Earnings (4)
Subsequent Section	-0.0335	-0.0465***	-0.0212*	0.0497*
	(0.0299)	(0.0165)	(0.0110)	(0.0274)
Course-Instructor-Term FE	Y	Y	Y	Y
Course-Time FE	Y	Y	Y	Y
Simulated 7:30 AM Section Probability FE	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y
N	7,570	4,393	3,186	3,143
R^2	0.237	0.081	0.245	0.157
Dependent Variable Mean	2.99	0.237	0.103	0.264

Notes: Each column represents a distinct student outcome for domestic students. Column 1 pertains to course grades. Column 2 focuses on the likelihood of students enrolling in STEM courses within the next two semesters. Column 3 examines students' major choices at the college level. Column 4 analyzes the first quartile of major-specific earnings. Columns 1 and 2 include observations of domestic, non-athlete freshman students aged 18–21 from Fall 2018 and Fall 2019. Columns 3 and 4 include observations of the domestic, non-athlete freshman cohort aged 18–21 from Fall 2018. Robust standard errors in parentheses are clustered at the individual and section levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.16: Class Start Times with Associated Time Gaps and Possible Prior Class Durations at Purdue University

Start Times	Class Lengths (Minutes)	Time Gaps (Minutes)	Possible Durations of Prior Classes (Minutes)
7:30 AM	50, 75, 110, 170	n/a	n/a
8:00 AM	50, 75, 80, 90, 170	n/a	n/a
8:30 AM	50, 110, 135, 150, 170	10	50
9:00 AM	50, 55, 75, 110, 130	10, 15, 40	50, 75
9:20 AM	120	0, 5, 30, 35, 60	50, 75, 80, 110
9:30 AM	50, 75, 90, 110, 125	0, 10, 15, 40, 45, 70	50, 75, 80, 90, 110
9:50 AM	90, 190	0, 20, 30, 35, 60, 65, 90	50, 75, 80, 90, 110
10:00 AM	90, 110, 120, 130, 135	5, 10, 30, 40, 45, 70, 75, 100	50, 55, 75, 80, 90, 110
10:30 AM	50, 75, 110, 140, 170	10, 15, 35, 40, 60, 70, 75, 100, 105, 130	50, 55, 75, 80, 90, 110, 170
11:00 AM	50, 75, 135	0, 10, 15, 40, 45, 65, 70, 90, 100, 105, 130, 135, 160	50, 55, 75, 80, 90, 110, 135, 150, 170
11:20 AM	55	0, 10, 20, 30, 35, 60, 65, 85, 90, 110, 120, 125, 150, 155, 180	50, 55, 75, 80, 90, 110, 120, 130, 135, 150, 170
11:30 AM	50, 75, 90, 110, 170	0, 10, 20, 30, 40, 45, 70, 75, 95, 100, 120, 130, 135, 160, 165, 190	0, 10, 20, 30, 40, 45, 70, 75, 95, 100, 120, 130, 135, 160, 165, 190
12:00 PM	50, 75, 110, 135, 170	0, 10, 15, 25, 30, 40, 50, 60, 70, 75, 100, 105, 125, 130, 150, 160, 165, 190, 195, 220	50, 55, 75, 80, 90, 110, 120, 125, 130, 135, 150, 170
12:10 PM	50	0, 10, 20, 25, 35, 40, 50, 60, 70, 80, 85, 110, 115, 135, 140, 160, 170, 175, 200, 205, 230	50, 55, 75, 80, 90, 110, 120, 125, 130, 135, 150, 170

Table A.12: Class Start Times with Associated Time Gaps and Possible Prior Class Durations at Purdue University

Start Times	Class Lengths (Minutes)	Time Gaps (Minutes)	Possible Durations of Prior Classes (Minutes)
12:15 PM	75	0, 5, 15, 25, 30, 40, 45, 55, 65, 75, 85, 90, 115, 120, 140, 145, 165, 175, 180, 205, 210, 235	50, 55, 75, 80, 90, 110, 120, 125, 130, 135, 150, 170
12:30 PM	50, 65, 75, 110, 170	10, 15, 20, 30, 40, 45, 55, 60, 70, 80, 90, 100, 105, 130, 135, 155, 160, 180, 190, 195, 220, 225, 250	50, 55, 75, 80, 90, 110, 120, 125, 130, 135, 150, 170
1:00 PM	65, 75, 90, 110, 140	0, 10, 15, 40, 45, 50, 60, 70, 75, 85, 90, 100, 110, 120, 130, 135, 160, 165, 185, 190, 210, 220, 225, 250, 255, 280	50, 55, 75, 80, 90, 110, 120, 125, 130, 135, 140, 150, 170, 190
1:10 PM	95, 190	10, 20, 25, 50, 55, 60, 70, 80, 85, 95, 100, 110, 120, 130, 140, 145, 170, 175, 195, 200, 220, 230, 235, 260, 265, 290	50, 55, 75, 80, 90, 110, 120, 125, 130, 135, 140, 150, 170, 190
1:30 PM	50, 75, 80, 90, 110	0, 10, 15, 30, 40, 45, 70, 75, 80, 90, 100, 105, 115, 120, 130, 140, 150, 160, 165, 190, 195, 215, 220, 240, 250, 255, 280, 285, 310	50, 55, 75, 80, 90, 110, 120, 125, 130, 135, 140, 150, 170, 190
1:45 PM	90	0, 10, 15, 25, 30, 45, 55, 60, 85, 90, 95, 105, 115, 120, 130, 135, 145, 155, 165, 175, 180, 205, 210, 230, 235, 255, 265, 270, 295, 300, 325	50, 55, 65, 75, 80, 90, 110, 120, 125, 130, 135, 140, 150, 170, 190
2:00 PM	75, 110, 135, 170	10, 15, 25, 30, 40, 45, 60, 70, 75, 100, 105, 110, 120, 130, 135, 145, 150, 160, 170, 180, 190, 195, 220, 225, 245, 250, 270, 280, 285, 310, 315, 340	50, 55, 65, 75, 80, 90, 110, 120, 125, 130, 135, 140, 150, 170, 190
2:30 PM	50, 75, 90, 110, 115	0, 10, 15, 25, 40, 45, 55, 60, 70, 75, 90, 100, 105, 130, 135, 140, 150, 160, 165, 175, 180, 190, 200, 210, 220, 225, 250, 255, 275, 280, 300, 310, 315, 340, 345, 370	50, 55, 65, 75, 80, 90, 110, 120, 125, 130, 135, 140, 150, 170, 190

Table A.12: Class Start Times with Associated Time Gaps and Possible Prior Class Durations at Purdue University

Start Times	Class Lengths (Minutes)	Time Gaps (Minutes)	Possible Durations of Prior Classes (Minutes)
2:50 PM	90, 170	0, 5, 20, 30, 35, 45, 60, 65, 75, 80, 90, 95, 110, 120, 125, 150, 155, 160, 170, 180, 185, 195, 200, 210, 220, 230, 240, 245, 270, 275, 295, 300, 320, 330, 335, 360, 365, 390	50, 55, 65, 75, 80, 90, 95, 110, 120, 125, 130, 135, 140, 150, 170, 190
3:00 PM	50, 75, 90, 110, 150	0, 10, 15, 30, 40, 45, 55, 70, 75, 85, 90, 100, 105, 120, 130, 135, 160, 165, 170, 180, 190, 195, 205, 210, 220, 230, 240, 250, 255, 280, 285, 305, 310, 330, 340, 345, 370, 375, 400	50, 55, 65, 75, 80, 90, 95, 110, 120, 125, 130, 135, 140, 150, 170, 190
3:25 PM	50	5, 10, 25, 35, 40, 55, 65, 70, 80, 95, 100, 110, 115, 125, 130, 145, 155, 160, 185, 190, 195, 205, 215, 220, 230, 235, 245, 255, 265, 275, 280, 305, 310, 330, 335, 355, 365, 370, 395, 400, 425	50, 55, 65, 75, 80, 90, 95, 110, 120, 125, 130, 135, 140, 150, 170, 190
3:30 PM	50, 75, 90, 110, 170	10, 15, 30, 40, 45, 60, 70, 75, 85, 100, 105, 115, 120, 130, 135, 150, 160, 165, 190, 195, 200, 210, 220, 225, 235, 240, 250, 260, 270, 280, 285, 310, 315, 335, 340, 360, 370, 375, 400, 405, 430	50, 55, 65, 75, 80, 90, 95, 110, 120, 125, 130, 135, 140, 150, 170, 190
4:00 PM	50, 75, 110, 170, 230	0, 10, 15, 40, 45, 60, 70, 75, 90, 100, 105, 115, 130, 135, 145, 150, 160, 165, 180, 190, 195, 220, 225, 230, 240, 250, 255, 265, 270, 280, 290, 300, 310, 315, 340, 345, 365, 370, 390, 400, 405, 430, 435, 460	50, 55, 65, 75, 80, 90, 95, 110, 120, 125, 130, 135, 140, 150, 170, 190

Table A.12: Class Start Times with Associated Time Gaps and Possible Prior Class Durations at Purdue University

Start Times	Class Lengths (Minutes)	Time Gaps (Minutes)	Possible Durations of Prior Classes (Minutes)
4:10 PM	55	10, 20, 25, 50, 55, 70, 80, 85, 100, 110, 115, 125, 140, 145, 155, 160, 170, 175, 190, 200, 205, 230, 235, 240, 250, 260, 265, 275, 280, 290, 300, 310, 320, 325, 350, 355, 375, 380, 400, 410, 415, 440, 445, 470	50, 55, 65, 75, 80, 90, 95, 110, 120, 125, 130, 135, 140, 150, 170, 190
4:30 PM	50, 75, 90, 100, 110	0, 5, 10, 15, 30, 40, 45, 70, 75, 90, 100, 105, 120, 130, 135, 145, 160, 165, 175, 180, 190, 195, 210, 220, 225, 250, 255, 260, 270, 280, 285, 295, 300, 310, 320, 330, 340, 345, 370, 375, 395, 400, 420, 430, 435, 460, 465, 490	50, 55, 65, 75, 80, 90, 95, 110, 115, 120, 125, 130, 135, 140, 150, 170, 190
5:00 PM	50, 75, 110, 120, 170	0, 10, 15, 30, 35, 40, 45, 60, 70, 75, 100, 105, 120, 130, 135, 150, 160, 165, 175, 190, 195, 205, 210, 220, 225, 240, 250, 255, 280, 285, 290, 300, 310, 315, 325, 330, 340, 350, 360, 370, 375, 400, 405, 425, 430, 450, 460, 465, 490, 495, 520	50, 55, 65, 75, 80, 90, 95, 110, 115, 120, 125, 130, 135, 140, 150, 170, 190
5:30 PM	50, 75, 80, 90, 110	0, 10, 15, 25, 30, 40, 45, 60, 65, 70, 75, 90, 100, 105, 130, 135, 150, 160, 165, 180, 190, 195, 205, 220, 225, 235, 240, 250, 255, 270, 280, 285, 310, 315, 320, 330, 340, 345, 355, 360, 370, 380, 390, 400, 405, 430, 435, 455, 460, 480, 490, 495, 520, 525, 550	50, 55, 65, 75, 80, 90, 95, 110, 115, 120, 125, 130, 135, 140, 150, 170, 190

Table A.12: Class Start Times with Associated Time Gaps and Possible Prior Class Durations at Purdue University

Start Times	Class Lengths (Minutes)	Time Gaps (Minutes)	Possible Durations of Prior Classes (Minutes)
5:45 PM	75	0, 5, 15, 25, 30, 40, 45, 55, 60, 75, 80, 85, 90, 105, 115, 120, 145, 150, 165, 175, 180, 195, 205, 210, 220, 235, 240, 250, 255, 265, 270, 285, 295, 300, 325, 330, 335, 345, 355, 360, 370, 375, 385, 395, 405, 415, 420, 445, 450, 470, 475, 495, 505, 510, 535, 540, 565	50, 55, 65, 75, 80, 90, 95, 110, 115, 120, 125, 130, 135, 140, 150, 170, 190
6:00 PM	50, 60, 75, 80, 90	0, 10, 15, 20, 30, 40, 45, 55, 60, 70, 75, 90, 95, 100, 105, 120, 130, 135, 160, 165, 180, 190, 195, 210, 220, 225, 235, 250, 255, 265, 270, 280, 285, 300, 310, 315, 340, 345, 350, 360, 370, 375, 385, 390, 400, 410, 420, 430, 435, 460, 465, 485, 490, 510, 520, 525, 550, 555, 580	50, 55, 65, 75, 80, 90, 95, 110, 115, 120, 125, 130, 135, 140, 150, 170, 190
6:10 PM	90, 170	0, 10, 20, 25, 30, 40, 50, 55, 65, 70, 80, 85, 100, 105, 110, 115, 130, 140, 145, 170, 175, 190, 200, 205, 220, 230, 235, 245, 260, 265, 275, 280, 290, 295, 310, 320, 325, 350, 355, 360, 370, 380, 385, 395, 400, 410, 420, 430, 440, 445, 470, 475, 495, 500, 520, 530, 535, 560, 565, 590	50, 55, 65, 75, 80, 90, 95, 100, 110, 115, 120, 125, 130, 135, 140, 150, 170, 190
6:30 PM	50, 75, 110, 170, 200	10, 15, 20, 30, 40, 45, 50, 60, 70, 75, 85, 90, 100, 105, 120, 125, 130, 135, 150, 160, 165, 190, 195, 210, 220, 225, 240, 250, 255, 265, 280, 285, 295, 300, 310, 315, 330, 340, 345, 370, 375, 380, 390, 400, 405, 415, 420, 430, 440, 450, 460, 465, 490, 495, 515, 520, 540, 550, 555, 580, 585, 610	50, 55, 65, 75, 80, 90, 95, 100, 110, 115, 120, 125, 130, 135, 140, 150, 170, 190

Table A.12: Class Start Times with Associated Time Gaps and Possible Prior Class Durations at Purdue University

Start Times	Class Lengths (Minutes)	Time Gaps (Minutes)	Possible Durations of Prior Classes (Minutes)
7:00 PM	50, 75, 110, 170	0, 10, 15, 40, 45, 50, 60, 70, 75, 80, 90, 100, 105, 115, 120, 130, 135, 150, 155, 160, 165, 180, 190, 195, 220, 225, 240, 250, 255, 270, 280, 285, 295, 310, 315, 325, 330, 340, 345, 360, 370, 375, 400, 405, 410, 420, 430, 435, 445, 450, 460, 470, 480, 490, 495, 520, 525, 545, 550, 570, 580, 585, 610, 615, 640	50, 55, 60, 65, 75, 80, 90, 95, 100, 110, 115, 120, 125, 130, 135, 140, 150, 170, 190
7:30 PM	50, 75, 170	0, 10, 15, 30, 40, 45, 70, 75, 80, 90, 100, 105, 110, 120, 130, 135, 145, 150, 160, 165, 180, 185, 190, 195, 210, 220, 225, 250, 255, 270, 280, 285, 300, 310, 315, 325, 340, 345, 355, 360, 370, 375, 390, 400, 405, 430, 435, 440, 450, 460, 465, 475, 480, 490, 500, 510, 520, 525, 550, 555, 575, 580, 600, 610, 615, 640, 645, 670	50, 55, 60, 65, 75, 80, 90, 95, 100, 110, 115, 120, 125, 130, 135, 140, 150, 170, 190
8:00 PM	50, 75	10, 15, 20, 30, 40, 45, 60, 70, 75, 100, 105, 110, 120, 130, 135, 140, 150, 160, 165, 175, 180, 190, 195, 210, 215, 220, 225, 240, 250, 255, 280, 285, 300, 310, 315, 330, 340, 345, 355, 370, 375, 385, 390, 400, 405, 420, 430, 435, 460, 465, 470, 480, 490, 495, 505, 510, 520, 530, 540, 550, 555, 580, 585, 605, 610, 630, 640, 645, 670, 675, 700	50, 55, 60, 65, 75, 80, 90, 95, 100, 110, 115, 120, 125, 130, 135, 140, 150, 170, 190, 230

Table A.12: Class Start Times with Associated Time Gaps and Possible Prior Class Durations at Purdue University

Start Times	Class Lengths (Minutes)	Time Gaps (Minutes)	Possible Durations of Prior Classes (Minutes)
8:30 PM	75	10, 15, 40, 45, 50, 60, 70, 75, 90, 100, 105, 130, 135, 140, 150, 160, 165, 170, 180, 190, 195, 205, 210, 220, 225, 240, 245, 250, 255, 270, 280, 285, 310, 315, 330, 340, 345, 360, 370, 375, 385, 400, 405, 415, 420, 430, 435, 450, 460, 465, 490, 495, 500, 510, 520, 525, 535, 540, 550, 560, 570, 580, 585, 610, 615, 635, 640, 660, 670, 675, 700, 705, 730	50, 55, 60, 65, 75, 80, 90, 95, 100, 110, 115, 120, 125, 130, 135, 140, 150, 170, 190, 230
9:00 PM	50, 75	0, 10, 15, 40, 45, 70, 75, 80, 90, 100, 105, 120, 130, 135, 160, 165, 170, 180, 190, 195, 200, 210, 220, 225, 235, 240, 250, 255, 270, 275, 280, 285, 300, 310, 315, 340, 345, 360, 370, 375, 390, 400, 405, 415, 430, 435, 445, 450, 460, 465, 480, 490, 495, 520, 525, 530, 540, 550, 555, 565, 570, 580, 590, 600, 610, 615, 640, 645, 665, 670, 690, 700, 705, 730, 735, 760	50, 55, 60, 65, 75, 80, 90, 95, 100, 110, 115, 120, 125, 130, 135, 140, 150, 170, 190, 230