Time-of-Day Effect on Academic Achievement of Adolescents

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ABSTRACT

This paper examines the relationship between time-of-day and academic performance of adolescent students. I use students' academic grade of their courses to measure their learning and performance. Applying multivariate regressions to a panel data set of 6870 Vietnamese first-year college students over a period of five years, I find that given a school start time, students whose lecture section meets in later time have higher performance than in the morning. However, the time effect varies significantly for different groups of subjects. My paper also concludes that the morning effect on academic outcomes diminishes over the week. The results are relevant to policies aiming to improve school efficiency and student productivity through rearranging course schedule.

I. Background and Motivation

Sleep affects many aspects of our life. Having a sufficient sleep helps us think and perform different tasks more efficiently and consistently. Furthermore, scientific studies have shown that sleep is crucial to several important memory, cognitive and performance-related functions. Insufficient sleep, however, can be harmful that impair many activities throughout a day. When hungry for sle ep, the brain tries to satisfy its need by causing the feeling of "sleepiness" that decrease levels of one's alertness and concentration. Excessive sleepiness is also associated with negative mood, inconsistent performance, lower productivity, and short-term memory that can inhibit learning ability and some behavioral controls (Curcio et al. 2006; Fallone et al. 2002).

In order to understand clearly how time of day can affect one's learning ability and productivity, it is important to understand the underlying biological process that regulates the sleep-wake cycles in humans. The circadian timing system, or circadian rhythm, provides a temporal organization that governs adaptive behavior, such as feeding, reproduction, and also sleep/wake cycles in humans. Crowley and other (2006) find that the circadian mechanisms govern the occurrence of sleep and sleepiness, subjective alertness and REM sleep within sleep. In addition to circadian rhythm, melatonin is a sleep-inducing hormone secreted by the human pineal gland that oscillates with a circadian rhythm. Research shows that levels of the hormone are mostly absent during the daytime when one feels awake, rise in the evening near one's usual bedtime, stay relatively constant during the nighttime, and decline near one's habitual wake-up time (Crowley, et al. 2006)

Adolescent development is followed by intense changes in patterns of sleep. It is found that these changes are the results from changes in psychosocial and lifestyle circumstances that accompany adolescence. For instance, at their stage of life, adolescents suffer from increasing school, family and social pressure (Curcio, et al. 2006). However, the maturation of biological processes that regulate the sleep and wake systems, such as circadian phase and melatonin secretion, may be strongly related to the sleep timing and amount during adolescence (Carskadon, 1993).

Research shows that the timing of melatonin secretion is significantly correlated to maturation and adolescents with melatonin secretion typically later in the day (Carskadon et al.

1997; Laberge et al., 2000). For instance, the secretion of melatonin for an average teen, which shifts two hours later than that of adults and children, starts after 11:00 p.m., peaks between 3:00 and 7:00 a.m. (i.e. the strongest circadian "dip" phrases), stops and then peaks again between 2:00 and 5:00 p.m. (Carskadon, Vieri, Acebo, 1993). Similarly, Wolfson and Carskadon (1998) find that melatonin levels, promoting sleep in humans, in adolescents rise in the evening and stay elevated throughout the night. Therefore, adolescents typically find it harder to sleep early at night. In fact, studies show that the typical high school student's natural time to fall asleep is 11:00 pm or later. (Wolfson and Carskadon, 1998). On average, like children, adolescents require as much sleep as 8.5 up to 9.25 each night (Carskadon et al., 1980). However, research shows that teens are more likely to experience daytime sleepiness, even when their schedule provides for optimal amounts of sleep. (Carskadon, Vieri, Acebo, 1993).

The sleep and circadian timing research provide two important predictions about time of the class and academic achievement of students. First, students who are assigned to early morning class are most likely sleep deprived since they do not have enough sleep as explained by the findings on sleep phase delay. Also, sleepy students tend to perform worse than the well-rested ones. Second, the circadian timing preference, influenced by the sleep phase delay of students, can change the learning ability and productivity of the students throughout the day. In particular, circadian cycles make people more sleepy or more alert at certain times of the day, with wakefulness likely to peak in the late morning, drop, and rise again in the afternoon. Therefore, adolescents' academic performance is expected to follow very similar time patterns which they will likely perform better if they feel more alert and wakeful.

II. Literature Review

Motivated by the studies on sleep loss, daytime sleepiness and circadian timing preference of adolescents as a result of sleep phase delay, my research question is whether there is a significant relationship between time-of-day and academic achievement of adolescent students, given a school start time. Specifically, my hypothesis predicts that students who attend early morning class will likely perform worse than those who take the same courses in different time slots. My research topic is relevant to three distinct literature.

The first strand of research deals with the circadian timing preferences of adolescents. Studying on the time of the day effect on cognitive function of adolescents, David Goldstein and the others (2007) find that scores on intelligence tests are significantly lower during the early morning hours, regardless of their timing preferences. Moreover, they find that adolescents, who take the cognitive test at a particular time different from their preferences tend to score lower than average. The effect is even worse for the "evening type" teenagers who take the exam in the morning.

Secondly, my paper is relevant to research on sleep and academic performance. Previous studies suggest that students who are sleep deprived tend to perform worse than those who are more well-rested. For instance, Wolfson and Carskadon's (2004) summary of a collection of self-reported surveys suggests that "shortened total sleep time" and "poor sleep quality" negatively affect the academic outcomes of adolescents from middle school through the college years. Curcio and other (2006) conclude that both the quality and quantity of sleep are closely related to student learning capacity and academic performance. Moreover, they suggest that sleep loss is frequently associated with poor declarative and procedural learning in students. Similarly, many studies also conclude that the number of hours of sleep is found to be associated with higher academic achievement (Eliasson et al. 2002; Taras and Potts-Datema 2005).

Finally, my paper is also relevant to the school start time literature. In many papers, early school start time results in waking up early that conflicts with the usual sleep-wake-cycles of adolescents. Given early school start time, it is found that adolescents prefer to go to bed late and sleep less. (Shinkoda and other, 2000). As a result, students attending class in these early time slots tend to be sleep deprived because of not having enough sleep before class (Wolfson and Carskadon, 2003). In studying the effect of class start time on academic outcomes of students, Carrell and other (2011) are able to find a significant positive effect of starting school 50 minutes later on academic achievement of a group of college freshmen, even controlling for other confounding factors that can affect student academic outcomes such as student, teacher and course characteristics. Similarly, Dills and Hernandez-Julian (2008) also supports the hypothesis that courses should meet later in the day in their empirical paper.

Similar to previous studies, my paper examines time-of-day effect on academic outcome of adolescents by performing multivariate regression analyses that also control for the possible confounding factors such as student's individual characteristics, teacher's effect, and classroom characteristics. Students taking certain courses in the earliest time slot offered is more likely sleep deprived. Moreover, most of these teenagers, due to the phase delay development, tend to be the "evening" type who are more awake and alert at later time of the day. Some previous studies experience serious problem that biases the effect of morning class timing on academic performance. In particular, self-selection arises when students know their time preference and choose courses at certain time of the day they likely perform best. Due to the randomization of students into their courses in my sample university, my paper can eliminate the self-selection problem that likely bias the time-of-day effects. However, I also perform formal randomization analysis to ensure that the students are randomly assigned to their courses. Moreover, my paper explores the time of the day effect on a different specific group of students since the data consists of a sample of Vietnamese students. In particular, the data consists of over 50,000 observations of individual course grades of their first semester from a private university in Vietnam over the period of five years. Courses offered can have start time as early as 6:30 am in the morning and as late as 3:05 p.m.. Also, exploiting the uniqueness of the university's schedule that each course is offered every day for a week and that first-year students only meet once a week for their courses, my paper also studies the interaction effect of attending morning classes and day the week on academic achievement of students. In addition to simply comparing the academic outcomes of student taking certain course early morning to those taking in later time slot, I also compare the student performance of different time slots throughout a day.

III. Data

My study requires extensive background information on individuals such as student's GPA, the courses they took, their meeting time, and their professors. The data source that I use is from a private university in Vietnam which I have access to individual-level data that contains extensive information on students such as the courses that they take in a semester, the meeting time, their final grades in that class, the professors with whom they take the course. The population which I am going to estimate is the sample of first-year college students from a period of five years, from 2011 to 2015. The college mainly offers majors in Technology and Economics. In this analysis, I focus primarily on the two groups of students.

Background: The university follows a semester system, similar to the U.S semester system in which school starts around September and ends around June. In the follow-up regressions, my paper focuses mainly on the group of courses that students take during their first semester in college. The two major programs offered at this university are in Technology and Economics related fields. In addition to the typical Bachelor's degrees, the university also offers Associated degrees upon completion of the two-year programs in both Technology and Economics fields. On average, students who enroll in the two-year program at this university are lower achievers compared to the traditional four-year undergraduates. Each year, approximately 2000 students are accepted to the university, including both groups. In this paper, I focus mainly on the group of four-year college students. The total number of four-year students collected from the period of five years is 6,780 students, of which 4005 are male and 2865 are female. Different from conventional universities, the university requires its first-year students to follow a rigorous academic curriculum established by the staff and faculty. That is, first-year students are not allowed to freely choose their courses and meeting times. Instead, they are randomly assigned to selected courses by the university's staff and faculty. That is, the randomization process of students to their courses follows the alphabetical order of their names (i.e. first letters of their first names), their majors and the courses they are enrolled in. Exploiting the randomization of students into their courses, my analysis can distinguish the effect of early morning time from student's individual time preference that affects their academic outcomes. For instance, "morning" and "evening" type students all have a random chance of being assigned to early morning lectures for the courses that they have. This randomized process will allow my paper to overcome the self-selection bias, where "morning" students will just select early morning courses that fit their timing preferences to optimize their performances and vice versa.

There are 21 courses offered for first-year students at this university, including discussions, practices and laboratory courses (i.e. Physics Laboratory Work). These courses also have instructors and meeting time like lectures. However, it is difficult to measure the change of student's learning ability throughout the day since outside-of-classroom work and assignments determine students' final grades in most of these laboratory courses. Therefore, I exclude these courses from my main analysis. However, I later include them in my robustness checks and the main estimate results are still robust.

Within their department, students have to take the major-specific courses. For instance, Marketing students in Economics department have to take a Web Design course in their first semester. However, there are some core subjects that students have to take regardless of their majors within a department. For example, the required courses for Technology first-year students are Math A2, Physics, Chemistry, and Foreign Language (i.e., Software Engineering, I.T and Web Development students within the same Technology department all need to take the core courses). Similarly, the core courses for Economics students are Math C1, English, and two Introductory Economics courses regardless of their majors within the Economics Department. I later apply the main regression estimate equation to study the effect of early morning on these specific subjects for both groups of majors.

In most of the courses, student's final semester grade is determined by the same final examination offered at the end of the semester. That is, students in different sections of the same course take the same final exams (i.e., student A and student B taking Math A1 in period 1 and 4 respectively also take the same final exam at the end of the semester). Similarly, grades in some other courses such as English and Sciences, also follow a standardized grading guideline that is the same across all sections of a course. Therefore, normalizing students' grades by course and year is sufficient to account for the differences across sections of the courses. In addition, their final grades also somewhat reflect their attendance throughout the semester since a portion of the grade includes pop quizzes which account for their attendance.

Table A shows the academic day schedule across five years of my sample. For the freshmen at this university, classes can start as early as 6:30 a.m. and as late as 3:05 p.m.. Each class period lasts 45 minutes, and there is a 5-minute or 10-minute break between each class. All courses usually meet for three periods each day. Each course is offered every day of a week, from Monday to Saturday. In their first year, students do not meet very frequently for each course that they take since they have to take many core subjects per semester. On average, each student takes four core subjects along with up to three other courses related to their majors. In addition, each class only meets once a week. On average, the duration for each class is between three and four periods long, which is about 2 hours 30 minutes up to 3 hours 20 minutes long, including breaks (see Table A).

Table 1 shows the summary statistics of my sample. The first column represents my entire sample statistics. The second and third column follow by comparing the mean and distribution of the independent variables between early and late periods. The mean grade in the first row is the raw GPA of the students in their respective courses, which scales from 0 to 10 in the Vietnamese Scoring System[1]. The summary suggests that on average, students have higher GPA on all of their courses when they meet later in the day. The second row uses normalized grade by courses to estimate student's academic performance. This approach more accurately reflects student outcome since grades across different courses vary significantly. The average normalized grades of students in the early morning periods is also lower than that of later time periods. This table also serves as a balancing test for my sample between the treatment group – courses that meet early in the morning – and the control group. There is no significant difference in the distribution of the independent variables between the two group periods. All of the variables are distributed somewhat evenly across early and late periods group. In my sample, approximately seven percent of the students come from minority ethnic group, 38 percent are female and about 17 percent are classified as low performing students by the staff and faculty. The average age of the students, which is about 18 years old, is also very similar across the early morning and other periods. The table also tells us the similar distribution of all courses during a week except for Saturday in which course lectures are more slightly distributed in later time slots.

Check for randomization of students to their courses: To uphold the validity of my results, I check students' pretreatment characteristics over each period to ensure that all students in different periods are similar in their background characteristics. In addition to the summary statistics table as a form of balancing test, I also plot several histograms to easily visualize how the distribution of different characteristics vary across periods. In this randomization checks, the four variables that explain the pretreatment characteristics are *age, gender, minority,* and *low-performing.* Figure 1A shows the distribution of mean age over periods. The graph shows that across periods, students are very similar in their age. The average age across all periods are about 18 years old. Figure 1B continues the randomization checks by plotting the distribution of gender over different periods of all courses. The gender ratio is also very similar across periods. The graph shows that on average the ratio is roughly 4 male to 3 female students in each period. It also reveals that period 1 and 4 tend to have the highest number of students being assigned to. This trend is because the university from year 2011-2013 was still under development in course

[1] In Vietnam, grade 5 out of 10 is roughly equivalent to the C range in the U.S system.

scheduling and so could only offer most classes on period 1 and 4. However, even there exists a difference in the student distribution, variable year fixed effect can control for the difference in year effect on academic outcomes of students. Moreover, figure 1B shows that the number of female students relative to the number of male students is very similar across periods. Similarly, figure 1C illustrates the distribution of minority ethnic group is somewhat constant across different times. Finally, figure 1D demonstrates that the distribution of lower-performing students tends to be higher in the early morning hours, especially in period 2.

Since not all figures show the distribution of student's characteristics is entirely the same across different times, I also perform a formal analysis to check if the randomization of students into their courses holds. This test also ensures that students' characteristics do not influence their decisions to take the courses. In other words, one should expect there is no relationship between the students' characteristics and the lecture time of their courses. I perform multivariate regression using *Early morning* variable as the dependent variable and all of the students' individual characteristics such as age, gender, whether they are in a minority group, and being classified as low-performing students as independent variables. I use the following multivariate regression to test for randomization:

$$Early_{ict} = \delta_0 + \delta_1 X_{ict} + \delta_2 Day_{ict} + \mu_t + \varepsilon'_{ict} \text{ (1)}$$

where $Early_{ict}$ is dummy period equal to 1 if student *i* attend early lecture of certain courses *c* in year *t*. X_{ict} includes all the aforementioned demographic variables of the students. Day_{ict}, day of the week fixed effect, will account for difference across days as each course only meets once a week. μ_i is the year fixed effect. ε'_{ct} is the random error term. I expect the coefficient δ_1 of the explanatory variable X_{ict} is statistically indistinguishable from 0, indicating the validity of randomization of students into their courses. Table 2A summarizes my findings: all of the coefficients of the independent variables are not significant, suggesting that all of the characteristics of a students do not influence how he or she chooses a certain course. The fourth row includes the F-test for joint significance of all coefficients. It appears that all coefficients are jointly insignificant given the estimate equation (1). I also apply the same regression estimates for different subgroups of subjects. There appears to be some selection into morning class; there are more students who are in minority ethnic group being assigned to Math

E and less lower-performing students being assigned to Sciences. Nonetheless, the results confirm that students cannot individually choose the selected courses to meet their time preference.

Check for randomization of professors to their courses: A plethora of studies interested in teacher quality on student academic achievement conclude that teachers do play a significant role in the performance of their students (Rockoff, 2004). Even with the professor fixed effect, early morning effect on student performance may be biased if lower-quality professors tend to select to teach in these hours (this will be explained later in the Results section). Therefore, to ensure that my paper captures the true effect of early morning on student's grade, I analyze if there is a randomization of professors into their courses. In particular, I examine whether higher-quality instructors are more likely to be assigned to early periods, or vice versa, by performing regressions on dummy variable for period early against different groups of professors. I use the following equation to test for randomization of professors:

$$Early_{ct} = \gamma_0 + \gamma_1 Q_{ct} + \gamma_2 Day_{ct} + \mu_t + \varepsilon''_{ct} \quad (2)$$

$Early_{ct}$ is an indicator variable equal to 1 if course *c* has lecture time in the early morning hours in year *t*. The vector Q_{ct} includes three different groups of professor regarding their quality and effectiveness in course *c* in year *t*. Day_{ct} is day of the week fixed effect. μ_t is year fixed effect and ε''_{ct} is the random error term. There should be no significant effect on each coefficient of the professor quality group. In this estimate, I characterize lower-quality professors, or those who are not very effective in teaching their respective courses, as those whose students' average normalized grade at the end of the semester is below the 25th percentile of the normalized grades by course[2]. Similarly, those who are in average-quality category have mean normalized score of their students above 25th percentile but below 75th percentile. The baseline that I compare to is the rest of higher-quality professors. Table 2B shows the results using equation (2) to examine the randomization of professors to their courses. In general, there is no significant evidence that professor's average quality influences their decision. However, the

[2] My data still lacks information on whether a professor is adjunct or full-time, which can influence the decisions on lecture time schedule. Since this approach uses student's normalized grade at the end of the semester to measure professor's effectiveness in teaching their courses, endogeneity problem may occur.

significant negative slopes on low-quality professors for both Math for Economics and Economics course suggest that selection of professors into their courses still occurs. Therefore, interpretation of the time-of-day effect on academic outcomes of students in these courses should be viewed more cautiously.

IV. Empirical Strategy

The main empirical specification I would like to estimate is the following multivariate regression equation:

$$Y_{ict} = \beta_0 + \beta_1 Early_{ict} + \beta_2 Day_{ict} + \beta_3 X_{ict} + \beta_4 s_{ict} + Prof_{ict} + \mu_t + \varepsilon_{ict} \quad (3)$$

Y_{ict} measures the academic outcome of the student. Y_{ict} is the final academic grade at the end of first semester of student *i* in course *c* of year *t.* For example, Y_{ict} includes the grade at the end of the semester of student A taking Chemistry 1 course in year 2010. In this paper, course *c* is a specific course of a subject. For example, Math subject has two courses, Math A1 and Math C1. The unit measure scales from 0 to 10, according to the Vietnamese grading system. However, in this paper, I normalize the grade of students by courses, with mean of 0 and standard deviation of 1, since different courses vary in characteristics such as their content and difficulty. Normalized grade allows me to distinguish clearly the early morning effect on the courses [3]. The main variable of interest is "*Early"* which is an indicator variable that is equal to 1 if the student takes certain courses early in morning. In my sample, the earliest and second earliest class start at 6:30 a.m. and 7:20 a.m. respectively (see Table 1). Therefore, to be in accordance with the previous studies on circadian phrase of adolescent literature that adolescent strongest circadian "dips" occur during these time slots, I let $Early_{ict}$ equal to 1 if the students take class in either of the first two morning time slots, period 1 or 2. The main coefficient of interest is β_1, which tells us the difference in learning between students who are randomly assigned in the morning and those who are randomly assigned to later time of the day.

[3] Regressions using student raw grade also produce similar results

I also include other controlling variables that can also affect academic outcomes. In the main regression equation, X_{ict} controls for individual characteristics such as gender, their age, whether they are in minority group[4], and if being classified as lower-performing student. In general, students from minority ethnic group has a more disadvantaged background in education. On average, they tend to be from families in the lower socioeconomics quantiles. Their parents are also less educated, and most students who are accepted to the university are the first-generation college students. In addition, my data also contains a variable that controls for student's pretreatment characteristic. That is, student's performance prior to being enrolled in college. The admission score[5] that determine students' eligibility consists of student's high school GPA, their entrance examination score or high school exit exam. However, the admission process has changed significantly from 2011 to 2015. Therefore, vector μ_t controls for time fixed effect like year fixed effect will help account for the differences and trends across years. The term s_{ict} controls for the classroom effect – a section of a course (i.e. Math 2A section 5) – to eliminate the across-classroom differences. In my sample, the term s_{ict} includes class size. Some previous studies try to estimate the causal relationship between class size and student's academic outcome. However, the results are not clear, especially for K-12 education (Hanushek, 1999). Even though most professors teach different sections of a course, some professors are assigned to the same course sections over the periods of five years. Therefore, I also include the term $Prof_{ict}$ that accounts for the difference in professor's quality, their grading style (i.e. some professors might be easier in their grading) and other characteristics. In particular, the variable that control for professor's effect on academic grade is the unique identifier for each professor for the courses they teach. Finally, ε_{ict} is the random error term.

I predict that β_1 is negative as having morning class is likely correlated with lower academic performance according to both the circadian timing preference and school start time literature: students are not well-rested and alert in the early morning. If the estimate of β_1 is statistically significant, it implies the causal relationship between the two variables "Grade" and "Early", controlling for all aforementioned variables.

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[4] In Vietnam, the majority ethnic group is the Kinh people. Other ethnicity groups are considered minority ethnic group.

[5] Due to data constraints, I do not have the exact admission score for each student. Instead, I have them categorized by their relative performance. For example, there are two groups: the average student group, whose admission scores are above certain threshold (established by the admission officers) and low-performing students, whose score are just below the threshold.

Different from previous literature studying on the relationship between morning effect and academic grade, my dataset allows me to study the potential effect of days of the week on academic achievement of student since students only meet once a week for each course they take. Therefore, my equation includes the term Day_{ict}, which accounts for day of the week effect. In particular, the vector controls for the day that student *i* have class *c* in year *t.* I include five distinct indicator variables Tuesday, Wednesday, Thursday, Friday and Saturday to control for day of the week effect. The omitted variable is Monday. There could be a negative relationship between day of the week and academic achievement since students tend to focus less on their study as it is closer to the weekend, which drives down their academic outcomes. Furthermore, I also allow the interaction term between early morning class indicator variable and the day of the week variable to examine whether morning effects are worse in later days of a week. One explanation is that students tend to spend time during their weekend catching up with sleep. Therefore, students tend to be more tired on Monday early morning because of having to wake up early in the morning again. I predict that the early morning effect on those students are worse in Monday relative to that in later days of the given week. The OLS regression is slightly different from the original equation (3) by including these interaction terms. Specifically, the equation is the following multivariate regression:

$$Y_{ict} = \beta'_0 + \beta'_1 Early_{ict} + \beta'_2 Day_{ict} + \beta'_3 Early_{ict} Day_{ict} + \beta'_4 X_{ict} + \beta'_5 s_{ict} + Prof_{ict} + \mu_t + \varepsilon_{ict} \quad (4)$$

Where the estimate of β'_1 now captures the early morning effect on academic grades of course that meets on Monday. The sum of coefficients β'_2 and β'_3 captures and compares the early morning effect on academic outcome of course that meet on the other day of the week to that of Monday. β'_3 tells us how different early morning effect is on the other day of the week relative to that of Monday. I predict that students who take early morning courses later in the week perform better than in the beginning of the week. Most students tend to catch up with their sleep amount over the weekends. Therefore, they tend to be more sleep deprived earlier in the week because of sudden change in both the quality and quantity of sleep right after their weekends. As day of the week goes, the negative effect of early morning on academic outcomes is likely mitigated as students cope better with their sleep deprivation.

VI. Results

In the following main regressions, I omit group of students who are older than 21 years old to examine the time of day effect on the group of adolescents more clearly. In Table 3, I perform regressions following the specification of equation (1). The first column of Table 3 follows a simple bivariate regression in which I regress the dependent variable, normalized grades by course, against morning periods to study the effect of attending morning class. Specification 2 follows by adding more control variables such as students' characteristics and the fixed effect of year. Specification 3 adds day of the week effect. The results from Table 3 suggest that there is a morning effect on the learning ability of students for all subjects. In particular, students who take courses in period 1 or 2, which starts at 6:30 a.m. or 7:20 a.m. respectively, have lower grade points than those who take the same courses in later periods on the same school day. Even though the effect is small, about 0.034 standard deviation of grade points lower, it is significant. The morning effect estimate does not move considerably when day of the week effect is also included in the column 3 of Table 2. For column 4, I include professor fixed effect to account for differences across professors to the model. The effect of attending lectures in early periods is the same: these students score 0.034 standard deviation points lower than those taking the same course in later time of day. Day of the week also appears to have some effect on the average academic grade of the students. However, the trend is not clear. Using mean grades on Monday as a baseline, students perform slightly worse on Tuesday and Wednesday. Although there is strong evidence on the effect of Tuesday and Wednesday on grade, there is no strong evidence that later days of the week have a significant impact on academic outcomes.

Table 4 represents the main regressions for selected subjects to analyze how early morning effect varies between subjects. Each column accounts for a different set of subjects. All specifications follow equation (3), the model without the interaction effect. Column 1 includes the entire sample, which is also the result from Table 3. Column 2 represents Math subjects by adding the average grade of all Math courses offered for Technology students such as Math A2 and Math A1. Column 3 is Math C1 for Economics students. Similarly, Column 4 represents the group of Sciences subject, including the average grade of both Chemistry and Physics courses for Technology students. Column 5 measures the effect of "Early" on grades of Non-STEMs subjects, which is English in my sample. Column 6 presents the morning effect on average grade of Economics courses. The effect of morning hours on grade of Math subjects are slightly significant. However, the magnitude is negative and larger compared to the baseline regression where all subjects are included (column 1). One explanation concerns with the wake-up effect. In particular, grades of Math depend mostly on the final exams that reflect learning ability of a student throughout the semester. The effect of early morning hours can impair the learning ability of a student during their meeting time. Sleepy students attending Math course in the early morning hours do not pay attention in class throughout the semester that affects their final grades. Furthermore, student attendance can also explain the results of Math subjects. It may suggest that students who take these courses in the morning tend to skip class because of not having enough sleep and weariness, which negatively affect their learning and performance. The evidence, however, is very different in Sciences and English courses. There are two explanations for the difference. First, grades in these courses may not be determined solely by final exams in these courses. For instance, a significant portion of their grade may consist of other assignments such as term papers, projects or laboratory work (Sciences and Physics lectures may require knowledge from the equivalent laboratory courses) that can be done outside of classroom. Therefore, the estimate of early morning does not reflect learning ability of students in these courses. Moreover, given that most of the course final grade depends on outside-of-classroom assignments, students simply skip class in the morning periods if they are sleep deprived and work on the assignments such as term papers later. Therefore, the morning effect most likely cannot explain the actual learning of Sciences and English courses.

Finally, even though the effect of the early morning seems significantly worse for Economics and Math E courses (column 3 and 6 respectively), it should be interpreted more cautiously. One problem is that the randomization test suggests less experienced professors, whose average score is in the lower quartile range, tend to select into teaching early morning lectures (see Table 2B). The estimates likely bias downwards the actual morning effect on grades. However, it is difficult to disentangle different mechanisms. For instance, less effective professors may tend to be adjunct professors who have less freedom in choosing their time slot for teaching. Most universities, at least in Vietnam, tend to prioritize full-time professors in selecting their own schedules, or likely to accept their timing preference requests. In my sample, at least for Math E and Economics courses, full-time professors may prefer to work at the later hours due to traffic in the early morning. Therefore, adjunct professors are more likely to be assigned to teach early morning lectures. Furthermore, adjunct professors likely change their status over time (i.e. adjunct professor A, who taught his course in 2013, gets promoted to full-time professor in 2014). Therefore, even with professor's fixed effect, the estimate on academic outcomes likely captures this trend as well, which likely underestimate the true effect of early morning hours. On the other hand, circadian rhythm may affect these low-quality professors as well as their students. Nonetheless, it is not likely the case since the circadian timing preference of most adults tends to be in the early morning hours.

VII. Extension Model

In the following extension regressions, I now allow different interactions to analyze how early morning hours effect varies with days of the week. In Table 5, the first column is the baseline result. The second column follows equation (4) specified earlier by allowing interactions between attending first period and day of the week that the course meets. The sum of coefficients of *Day* and *Day* × *Early* reveal how early morning effect varies throughout a week. The interpretation of *Early* estimate now tells us the Monday's morning effect on grade. The estimate magnitude is much larger than that of the baseline regressions, suggesting that students are most likely sleep deprived on Monday morning. The table also reveals a negative effect of day of the week on adolescent's academic outcome. However, the interpretation is different. The estimates on *Day* (i.e. *Tuesday*) now compare the relative academic performance of students in their late courses across different days. Furthermore, all of the interaction effects are statistically significant. Even though the direction of the trend is not clear, the results reveal that students who take courses in early periods on Tuesday and Wednesday perform worse than those taking early classes on Monday. However, students perform better in early courses if they meet on later day of the week, from Thursday to Saturday, relatively to earlier days of the week. This finding suggests that the negative effect of early morning hours on grades seems to diminish over the week. One explanation for this trend is that adolescents tend to sleep more over the weekend to catch up on sleep. Having early morning class on Monday disrupts both the quality and quantity of sleep, which they have to suddenly reduce to wake up early and attend class. However, as day goes by throughout the week, they seem to cope better with the stress of having to wake up early and attend morning classes.

In addition to simply examine the overall effect of early morning hours on grades, I change the independent variable “Early” to different points of time on an academic day to study how student’s learning ability change throughout a day. This estimation alters the main equation (3) by allowing different dummies for different time slots of lecture and comparing them to the baseline 6:30 a.m. (period 1). Figure 2 captures my results. The average grade of students taking courses in the earliest hour (6:30 a.m.) is normalized to 0. Overall, the results are in accordance with literature on circadian rhythm timing of adolescents. In particular, adolescent learning ability seems to peak at 8:15 a.m.., when their circadian “dip” phrase just ends and become more alert and wakeful. However, there is no strong evidence that later time in the morning, for example 9:05 a.m., is associated with higher grade. Furthermore, students are most productive in the afternoon, which is at 1:20 p.m.. However, I find no strong evidence that students whose lectures meet late in the afternoon, which is after 3:30 p.m. in my sample, perform better than in the morning.

VIII. Subgroups

Girls and boys have very different sleep patterns and habits. In particular, girls run on slightly different schedules than boys do. Research on gender difference in sleep shows that girls find that girls are more likely to be “morning” people; they are more likely to go to bed earlier and wake up earlier (Tsai, 2004). Therefore, given early schedule in the morning, it is implied that girls and boys will perform differently in their courses. Using the same estimate equation (3), I split the sample by gender and perform separate regressions to study the different effects of school start time on male and female students. Table 5 summarizes the effect of attending morning classes on academic outcomes of different subgroups in my sample. In addition to analyze how time of day effect varies by different subsets of the sample, the table also performs sensitivity analyses of the main results to different groups. The first two columns show how early morning time affects academic achievement of male and female students. The results suggest that the negative effect of morning time is significant in both groups. However, the effect seems larger and more significant for girls. On average, girls score 0.05 standard deviation of grade lower than their peers when taking morning courses while boys score 0.03 standard deviation lower. My results reveal that girls seem to be affected more if attending lectures in the early morning hours. However, there is no strong evidence that the morning effect on two group is different[6].

Next, I split my sample to different age group. The last two columns follow by examining the time-of-day effect on academic outcomes of different age groups: the typical age range for adolescence, which is either 17 or 18 years old, and the late adolescents, whose age ranges from 19 to 21 years old. Both age groups also have lower grades if being assigned to early morning courses. However, the negative morning effect on grades seems to be larger for the older age groups. This suggests that older adolescents do not cope as well relative to their younger counterparts to the stress of sleep deprivation. Although there seems to be a difference between both age group, it is not significant[7].

IX. Robustness Checks

Table 7 performs robustness checks for my equation estimate by alternating the model. All of the specifications follow equation (3), the estimated model without interaction effect on day of the week and early morning hours. The dependent variable is the slope coefficient on early periods the equation. Column 1 shows the main results. Column 2 follows by adding the second-degree polynomial of the variable age. Column 3 includes the laboratory courses that are omitted from the main regressions. The absolute value of the coefficient magnitude is moderately larger than that of the baseline regression, which suggests that there is a negative effect of early morning hours on these laboratory and discussion courses as well. Column 4 restricts the sample to majority ethnic group only. Similarly, column 5 restricts my sample to group of low-performing student. All of the estimates are somewhat stable across different specifications. Furthermore, all of them are significant and reveal that there is a negative effect of early morning hours on grades. Overall, the main estimate results is robust to different alternative equations, with subtle variation in the magnitude, ranging from 0.030 to 0.040 standard deviation.

[6] I perform two-sample t-test on early morning slope for the gender group and find no significant evidence that the coefficients on early morning are different between female and male. The p-value for the difference is 0.294

[7] Again, the two-sample t-test for the two age groups shows no significant evidence that the coefficients on early morning are different. The p-value for the difference is 0.632.

X. Discussion and Limitations

Even though my paper finds some evidence on time-of-day effect on academic outcomes of adolescents, several points should be discussed. First, the course lecture distribution to different time slot is still limited in this sample university. In particular, many of the courses are assigned to the 6:30 a.m. and 9:05 a.m. time slot (period 1 and 4) across 5 years. When restricting my sample to analyze the time effect on the two periods, I find no significant evidence that the grades are different between the two groups. The result suggests that students do not perform better in the late morning. Part of this trend is because the university is under development regarding the course scheduling. They are still expanding their course schedule to offer more time slots for each course throughout the day. It is not until 2014 that the university starts assigning more lecture times in the afternoon. Therefore, future data improvement on this will help solve the unbalanced distribution of courses over time slots.

Second, as discussed earlier, both the circadian timing and sleep amount are important for the productivity of students. The results of my paper are consistent with the circadian timing preference of adolescents. In particular, the academic outcomes of these students are expected to follow similar trends as the circadian "dip" phrases end. However, it does not say much about the relationship between sleep and grades. This paper assumes fixed amount of sleep among students. That is, given early lecture hours, all students do not have a sufficient sleep the night before and are sleep deprived while students who attend afternoon courses are more likely well-rested. Therefore, I cannot distinguish between students who are more sleep deprived than the other to estimate the relationship between sleep quality and academic achievement. For example, student A takes a course in the early morning, and student B takes the same course in the afternoon hours. This paper assumes B is more well-rested. However, in practice, both A and B may sleep an average of 5 hours and are both likely to experience daytime sleepiness. Therefore, the results on higher average grade in the later time courses does not say much about sleep quality and academic performance. Even though it is difficult to implement, data on sleep amount of students is helpful in distinguishing different mechanisms of early morning hours on academic achievement of adolescents.

Finally, data on student's attendance for each course is also useful to determine the true effect of early morning on grades. Students who often skip class are likely to perform worse than their peers do. Furthermore, students who are enrolled in morning courses are more likely to skip lectures because of either sleeping in or traffic. If this is the case, the estimate results in this paper likely underestimate the true effect of early morning hours on grades. On the other hand, some students may also choose to skip more classes if their courses meet later in the day so they can spend more time doing other enjoyable activities. Under this scenario, the estimate of early morning effect on academic outcomes likely overestimate the true effect.

XI. Conclusion

The results of my paper confirm the results from some previous studies on the circadian rhythm and timing preference of adolescents. Firstly, my paper concludes that on average, students who are assigned to early morning courses perform worse than in later time of day. In particular, students perform significantly worse the earlier the class starts: Those who take certain courses at 8:15 a.m. perform better than at 6:30 a.m.. and 7:20 a.m.. respectively. This is in accordance with the circadian rhythm studies that these time slots were particularly adverse to students' academic outcomes. However, my paper finds that the two peak time slots where student perform best are 8:15 a.m. and 1:20 p.m.. In addition, I find no significant evidence that students perform better in the late morning, from 9:00 a.m. until before noon. The exact magnitude of attending lectures in the early morning hours on grade is not clear, which can vary between 0.03 to 0.07 standard deviation lower, depending on different specifications. Furthermore, the time-of-day effect also varies significantly between different subjects.

My paper also concludes that the negative early morning effect on academic outcomes of adolescents significantly diminishes over the week. For example, students who are assigned to Friday early morning course earn higher grades than if being assigned to Monday morning course. This trend in day of the week suggests that some rearrangements of course schedule can be done to optimize the academic performance of students in each course. Some high schools and universities face constraint on resources that prevent them from alternating the lecture time of some courses. For instance, the available schedules of teachers may be limited to a particular time of day (i.e. some professors prefer to work in the morning). A simple exploitation can be done to take advantage of time-of-day and day of the week effect such as organizing different courses to different days to further increase productivity of students. For example, discussions and laboratory courses such as Chemistry Lab can be offered in the early morning hours on Monday. On the other hand, courses that require more on cognitive or memory function such as Economics and Math courses (Table 4 shows significant negative effect of taking early morning lectures for these courses), can be offered in the early morning hours in later days of the week.

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APPENDIX

TABLE A – CLASS SCHEDULE

	Period	***Start Time***	-	***End Time***
Morning	Period 01	06 : 30	-	07 : 15
	Period 02	07 : 20	-	08 : 05
	Period 03	08 : 15	-	09 : 00
	Period 04	09 : 05	-	09 : 50
	Period 05	10 : 00	-	10 : 45
	Period 06	10 : 50	-	11 : 35
Afternoon	Period 07	12 : 30	-	13 : 15
	Period 08	13 : 20	-	14 : 05
	Period 09	14 : 15	-	15 : 00
	Period 10	15 : 05	-	15 : 50
	Period 11	16 : 00	-	16 : 45
	Period 12	16 : 50	-	17 : 35

TABLE 1 – SUMMARY STATISTICS

	Full Sample Mean	*Early Periods Mean*	*Late Periods Mean*
All Courses Grade	5.66	5.56	5.71
	[2.27]	[2.32]	[2.25]
Normalized Grade	0.00	-0.01	0.01
	[1.00]	[1.02]	[0.99]
Age	18.30	18.31	18.30
	[0.82]	[0.86]	[0.79]
Female	0.38	0.36	0.39
	[0.49]	[0.48]	[0.49]
Minority Ethnic Group	0.07	0.07	0.07
	[0.26]	[0.26]	[0.26]
Low-Performing Student	0.17	0.19	0.16
	[0.38]	[0.39]	[0.37]
Class Size	45.63	45.91	45.48
	[16.16]	[16.37]	[16.06]
Tuesday	0.18	0.18	0.18
	[0.38]	[0.38]	[0.38]
Wednesday	0.17	0.18	0.17
	[0.38]	[0.38]	[0.38]
Thursday	0.18	0.19	0.18
	[0.39]	[0.39]	[0.38]
Friday	0.15	0.16	0.15
	[0.36]	[0.37]	[0.36]
Saturday	0.12	0.08	0.15
	[0.33]	[0.28]	[0.35]

Notes: Standard deviations are in brackets. The early periods sample include courses that start in period 1 or 2, while late periods are the other periods, 3 – 10. The full sample includes 50339 observations, of which 17027 are from early periods and 33312 are from late periods.

TABLE 2A – RANDOMIZATION CHECKS FOR STUDENT CHARACTERISTICS

VARIABLES	(1) *Full Sample*	(2) *Math T*	(3) *Math E*	(4) *Sciences*	(5) *English*	(6) *Economics*
Age	-0.002	0.008	-0.004	0.001	0.003	0.015
	[0.003]	[0.006]	[0.013]	[0.007]	[0.007]	[0.011]
Female	-0.029*	-0.070	-0.045*	0.050	-0.028	0.012
	[0.016]	[0.052]	[0.025]	[0.055]	[0.038]	[0.018]
Minority	0.013	-0.054**	0.082**	0.035	0.015	0.002
	[0.010]	[0.026]	[0.033]	[0.030]	[0.027]	[0.029]
Low performing	0.007	0.023	-0.037	-0.057**	0.029	-0.010
	[0.009]	[0.023]	[0.025]	[0.022]	[0.022]	[0.021]
P-value of Joint Significance for all coefficients	0.155	0.168	0.025	0.122	0.606	0.619
Observations	50,343	7,515	2,223	7,516	6,882	3,424
R-squared	0.023	0.152	0.067	0.027	0.093	0.066

Robust standard errors in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The dependent variable is *Early morning*, an indicator variable equal to 1 if the course lecture meet in either period 1 or 2, and to 0 otherwise. Math T is Math for Technology students. Math E is Math for Economics students. All specifications follow equation (1). The standard errors clustered at course section-by-year level are in brackets.

TABLE 2B – RANDOMIZATION CHECKS FOR PROFESSOR QUALITY

VARIABLES	(1) *Full Sample*	(2) *Math T*	(3) *Math E*	(4) *Sciences*	(5) *English*	(6) *Economics*
Average-quality	0.035	-0.064	-0.163	0.032	-0.009	0.049
professor	[0.025]	[0.082]	[0.170]	[0.099]	[0.082]	[0.089]
Low-quality	0.033	-0.017	0.390**	0.070	0.029	0.423***
professor	[0.039]	[0.121]	[0.152]	[0.118]	[0.126]	[0.136]
Observations	50,343	7,515	2,223	7,516	6,882	3,424
R-squared	0.030	0.182	0.128	0.059	0.115	0.148

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

<u>Notes:</u> The dependent variable is *Early morning*, an indicator variable equal to 1 if the course lecture meets in either period 1 or 2, and to 0 otherwise. Math T is Math for Technology students. Math E is Math for Economics students. All specifications follow equation (2). The standard errors clustered at course section-by-year level are in brackets.

TABLE 3 – FULL SAMPLE REGRESSION

Variables	(1) *Normalized Grade*	(2) *Normalized Grade*	(3) *Normalized Grade*	(4) *Normalized Grade*
Early morning	-0.003	-0.034***	-0.036***	-0.034***
	[0.010]	[0.009]	[0.010]	[0.010]
Age		-0.075***	-0.074***	-0.068***
		[0.018]	[0.018]	[0.017]
Female		0.198***	0.198***	0.202***
		[0.019]	[0.019]	[0.019]
Minority		0.031	0.031	0.044
		[0.034]	[0.034]	[0.034]
Low performing		-0.162***	-0.161***	-0.148***
		[0.024]	[0.024]	[0.024]
Class size		0.004***	0.004***	0.005***
		[0.001]	[0.001]	[0.001]
Tuesday			-0.052***	-0.038**
			[0.015]	[0.017]
Wednesday			-0.003	-0.042***
			[0.015]	[0.016]
Thursday			-0.048***	-0.009
			[0.015]	[0.017]
Friday			-0.044***	0.020
			[0.015]	[0.018]
Saturday			-0.050***	0.038*
			[0.016]	[0.020]
Observations	40,584	40,584	40,584	40,584
R-squared	0.000	0.052	0.053	0.111
Year FE		X	X	X
Teacher FE				X

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable in each specification of the table is the normalized grade of the course mean 0 and standard deviation of 1. *Early morning* is an indicator variable equal to 1 if students taking courses in either periods 1 or 2, and to 0 otherwise. The standard errors clustered at student-level are in brackets.

TABLE 4 – REGRESSION BY SUBJECTS

VARIABLES	(1) *Full Sample*	(2) *Math T*	(3) *Math E*	(4) *Sciences*	(5) *English*	(6) *Economics*
Early morning	-0.034***	-0.056*	-0.126**	-0.028	-0.037	-0.205***
	[0.010]	[0.029]	[0.052]	[0.024]	[0.026]	[0.037]
Observations	40,584	7,449	2,205	7,450	6,808	3,396
R-squared	0.112	0.138	0.096	0.148	0.237	0.142
Year FE	X	X	X	X	X	X
Teacher FE	X	X	X	X	X	X

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

<u>Notes:</u> *Early morning* is an indicator variable equal to 1 if students taking courses in periods 1 or 2, and to 0 otherwise. The dependent variable of all specifications is the normalized grades by courses and year for each subject with mean 0 and standard deviation of 1. All specifications follow equation (3). The standard errors clustered at student-level are in brackets.

TABLE 5 – INTERACTION EFFECT

VARIABLES	(1) *Normalized Grade*	(2) *Normalized Grade*
Early morning	-0.034***	-0.125***
	[0.010]	[0.021]
Tuesday × Early		0.057**
		[0.028]
Wednesday × Early		0.089***
		[0.029]
Thursday × Early		0.147***
		[0.028]
Friday × Early		0.140***
		[0.030]
Saturday × Early		0.159***
		[0.037]
Tuesday	-0.038**	-0.059***
	[0.017]	[0.020]
Wednesday	-0.042***	-0.074***
	[0.016]	[0.019]
Thursday	-0.009	-0.064***
	[0.017]	[0.020]
Friday	0.020	-0.034*
	[0.018]	[0.021]
Saturday	0.038*	-0.017
	[0.020]	[0.023]
Observations	40,584	40,584
R-squared	0.109	0.110
Year FE	X	X
Teacher FE	X	X

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: *Early morning* is an indicator variable equal to 1 if students taking courses in periods 1 or 2, and to 0 otherwise. The dependent variable of all specifications is the normalized grades by courses and year for each subject with mean 0 and standard deviation of 1. All specifications follow equation (4). The standard errors clustered at student-level are in brackets.

TABLE 6 – REGRESSION BY SUBGROUPS

Variables	(1) *Female*	(2) *Male*	(3) *17-18 Age Group*	(4) *19-21 Age Group*
Early morning	-0.051***	-0.029**	-0.032***	-0.046*
	[0.017]	[0.012]	[0.011]	[0.023]
Observations	16,178	24,406	32,591	7,993
R-squared	0.127	0.094	0.111	0.124
Year FE	X	X	X	X
Teacher FE	X	X	X	X

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: *Early morning* is an indicator variable equal to 1 if students taking courses in periods 1 or 2, and to 0 otherwise. The dependent variable of all specifications is the normalized grades by courses and year for each subject with mean 0 and standard deviation of 1. All specifications follow equation (3). The standard errors clustered at student-level are in brackets.

TABLE 7 – ROBUSTNESS CHECKS

VARIABLES	(1) *Full Model*	(2) *Age 2nd Degree Polynomial*	(3) *Lab Courses Included*	(4) *Low-Performing Excluded*	(5) *Minority Ethnic Group Excluded*
Early morning	-0.034***	-0.033***	-0.042***	-0.030***	-0.034***
	[0.010]	[0.010]	[0.009]	[0.011]	[0.010]
Observations	40,584	40,584	50,339	33,223	37,681
R-squared	0.109	0.110	0.096	0.115	0.110
Year FE	X	X	X	X	X
Teacher FE	X	X	X	X	X

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: *Early morning* is an indicator variable equal to 1 if students taking courses in periods 1 or 2, and to 0 otherwise. The dependent variable of all specifications is the normalized grades by courses and year for each subject with mean 0 and standard deviation of 1. All specifications follow equation (3). The standard errors clustered at student-level are in brackets.

FIGURE 1A – Histogram of Mean age over Periods

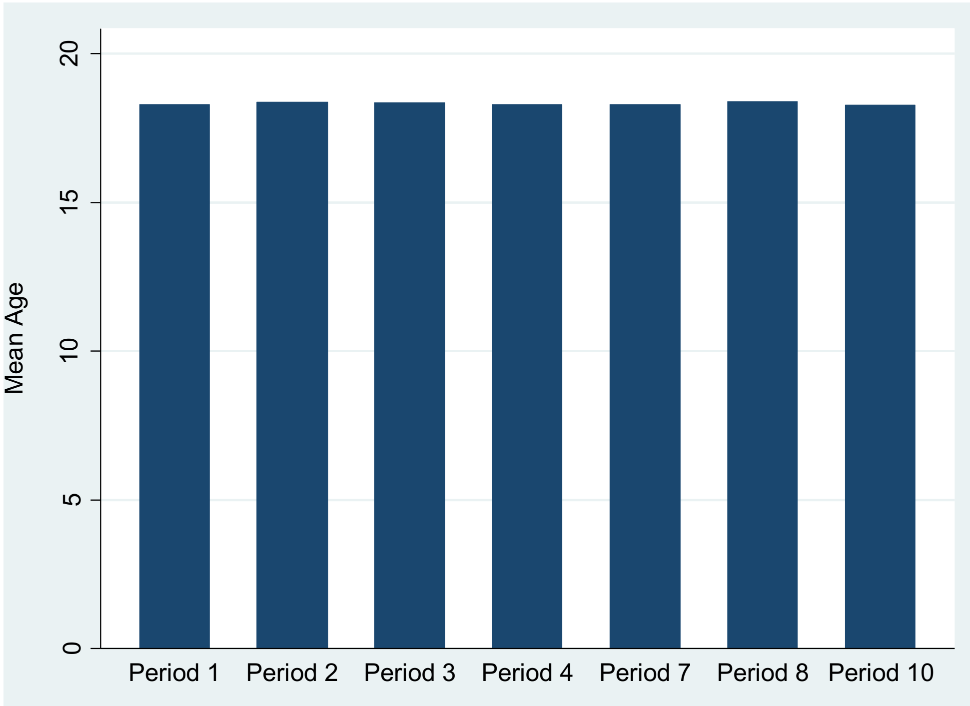

FIGURE 1B – Distribution of Gender over Periods

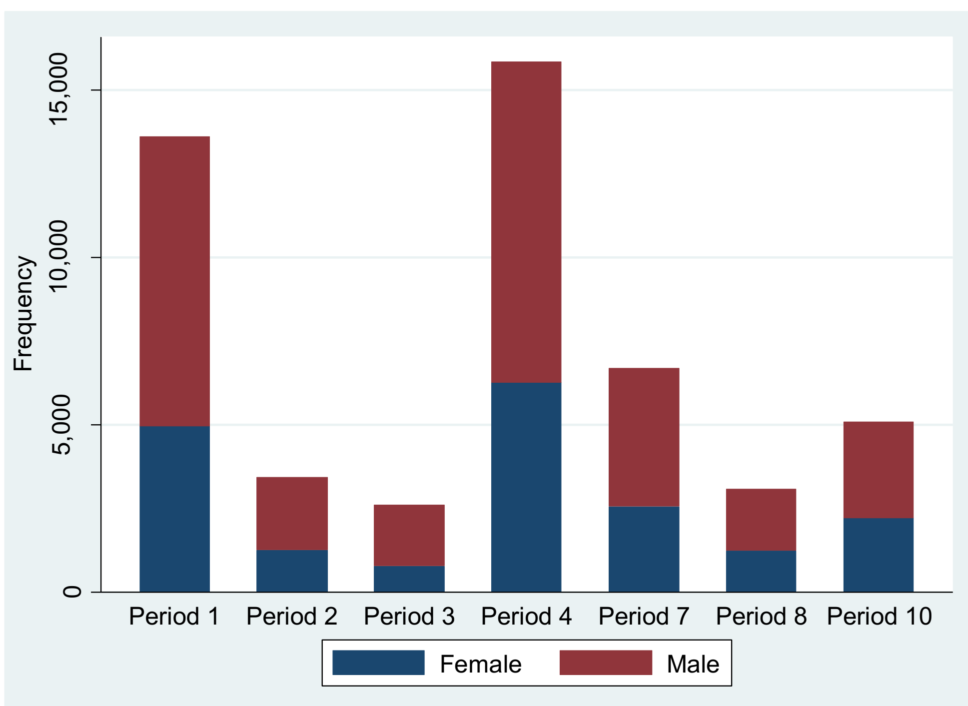

FIGURE 1C – Distribution of Minority Ethnic Group over Periods

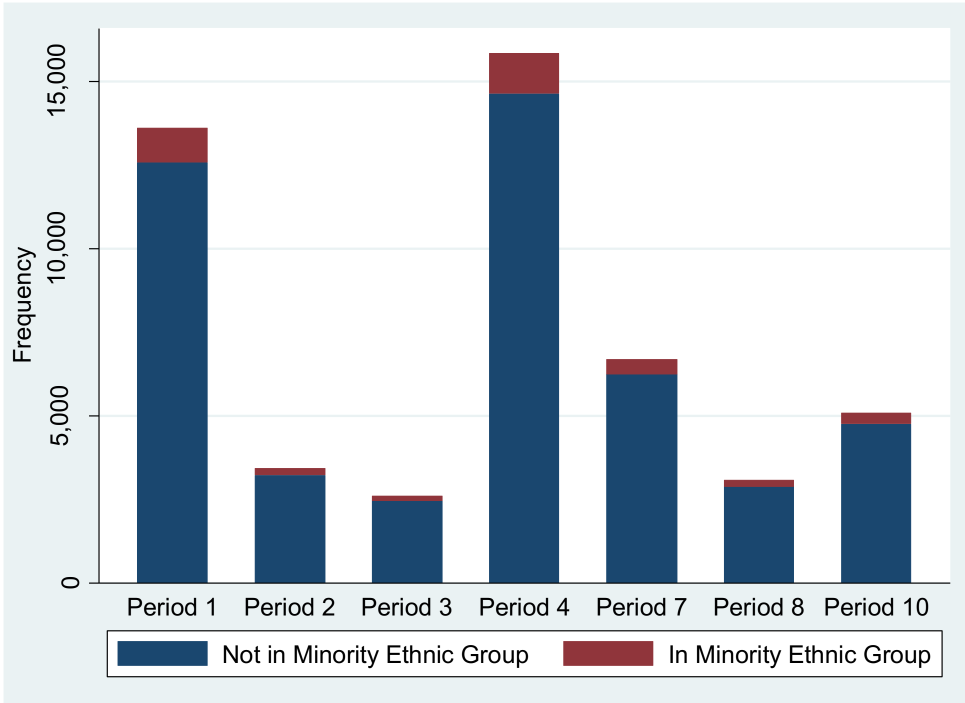

FIGURE 1D – Distribution of Low-Performing Group over Periods

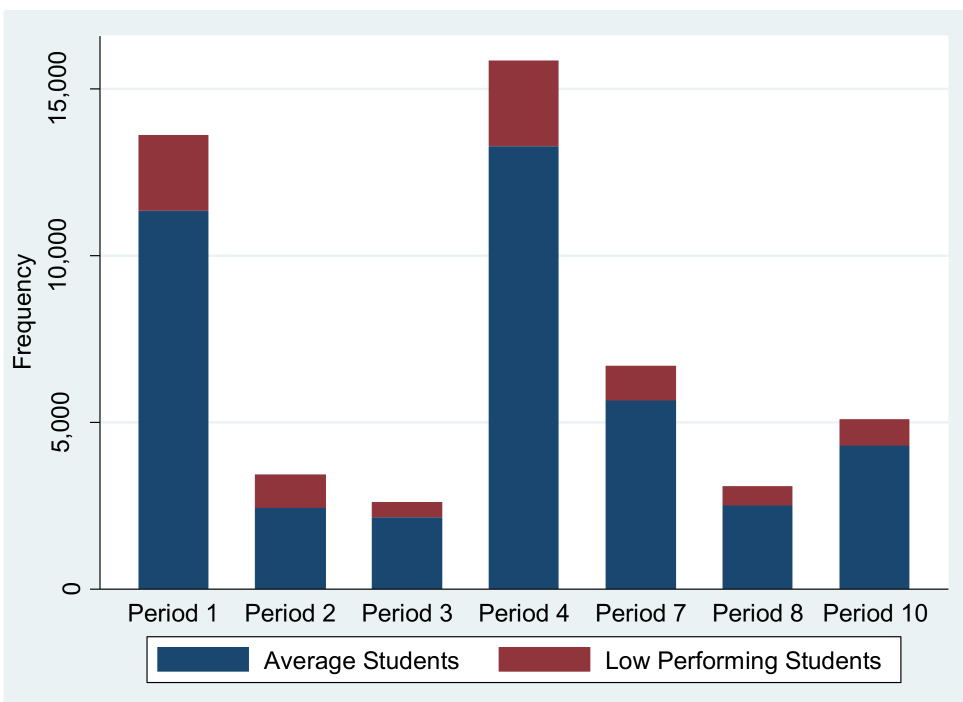

FIGURE 2 – STUDENT GRADES OVER TIME OF DAY