Class Scheduling and Student Performance in Economics Principles

By

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Dedicated to

My parents for the unconditional support

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ABSTRACT

This dissertation consists of three chapters.

In the first chapter titled “Do Morning Classes Improve Student Learning of Microeconomics Principles?”. This article analyzes the impact of class start time on students’ grades by using data from Middle Tennessee State University. The data cover a period of six years and are based on a sample of 5,803 individuals who enrolled in 133 sections of principles of microeconomics. To identify the causal impact of class start time on students’ grades, I used a Bootstrapping method which allowed assigning measures of accuracy to sample estimates. For males, the estimated coefficients were negative and statistically significant at the 10 percent level, and the coefficients suggested that a male student in an afternoon class could expect to earn a letter grade that is 0.029 GPA lower than he would have earned by taking the class in the morning. For females, the estimated coefficients were not statistically significant.

In the second chapter, titled “Does Meeting Once a Week Harm Students' Grades? A Comparison of Outcomes in Economics Classes”. This study of course scheduling, term length, and students’ grades in microeconomics principles is motivated by questions of whether (1) student learning differs across scheduling formats including one, two, and three days per week over traditional semesters; and (2) student learning differs by length of term. The results show that meeting more times a week over a traditional semester leads to higher student achievement. Furthermore, there is no difference in student performance in compressed terms compared to traditional 14-week terms. These results hold after controlling for factors expected to impact student's grades, such as student and

class characteristics. The results should interest university administrators who are responsible for course scheduling decisions, faculty who teach different course sections, and students planning their class schedules.

In the third chapter, titled “The Effects of Time Spent Online on Student Achievement in Hybrid Principle of Microeconomics Courses”. We study the determinants of academic achievement in Hybrid courses in principles of microeconomics. We retrieve the real time each student spent on exams and homework from MyEconLab and analyze the impact of that time on students' final grades. Time is a significant determinant of exam scores and final grades; more time spent online is associated with higher scores and grades. An additional hour spent on online exams improves a student’s grade by 0.42 GPA. This could change a student’s grade from a B+ to an A. If a student spends 5 hours more on online homework, it would improve that student’s grade by 0.34 GPA. This could change a student’s grade from a C+ to a B. We also investigated the determinants of the scores on each exam as a function of time spent on the exam and time spent on the homework leading to that exam. A one minute increase in time spent on an online exam improved exam score by 0.79 when using ACT score to control for ability. When using GPA to control for ability; the estimated coefficient on exam time is positive and statistically significant at the 1 percent level; a one minute increase in time spent during an online exam improved exam score by 0.83. Exam scores may be non-linearly related to time spent on an exam.

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CHAPTER I: DO MORNING CLASSES IMPROVE STUDENT LEARNING OF MICROECONOMICS PRINCIPLES?

Introduction

Grades and student achievement are important from an economic point of view because they have been shown to be related to measures of later adult success. Cameron and Heckman (1993), Murnane et al. (1995), and Currie and Thomas (1999) all show evidence of a great significance of early development in explaining differences in schooling and adult labor market outcomes in the US. Public and private colleges are always looking for innovation that increases productivity and produces more academically prepared students. This paper proposes a simple novelty that universities can use to improve student performance: rearranging course times to morning can increase academic performance by taking advantage of time of day effects.

The purpose of this article is to estimate the effect of class start time on a student’s grade. If class start time has an effect on student performance, this issue needs to be studied to find ways to improve students’ grades. This paper contributes to the existing literature on time of day and student achievement. No other studies have focused exclusively on microeconomics classes. Furthermore, the current literature is dated, and this paper updates this information about time of day and student achievement. I hypothesize that morning classes will display higher grades for both male and female students, as compared to their peers registered in later class times. Differences in the performance of students with different class times may arise because of student characteristics, class characteristics, and differences in the selection mechanisms for morning and afternoon classes. I examine the effect of student characteristics and account for the possibility that higher achieving students may generally register in early morning classes.

If a significant difference in student performance in morning over afternoon class times is found, this suggests ways to improve students' grades. Furthermore, this article examines the effect of morning productivity and student achievement. My study answers the question of whether students could expect to earn lower grades in afternoon sections of microeconomics principles (MICRO) than they would have earned by taking the class in the morning. The literature suggests that female students outperform male students and that females are more inclined to morning productivity over their male peers. This finding might raise questions of why males lag behind females in class grades. Goldin, Katz, and Kuziemko (2006) showed that the ratio of males to females graduating from a four-year college started to decline by 1980 and continued to decline to 0.74 in 2003. Therefore, there were 1350 females for every 1000 males who graduated from a four-year college by 2003.

I analyze data from the Office of Institutional Effectiveness, Planning, and Research (IEPR) at Middle Tennessee State University (MTSU), in a sample of 5803 students who took MICRO from many different instructors. I found that a male student in an afternoon class could expect to earn a letter grade that is 0.029 GPA lower than he would have received in a morning class. In contrast, for female students the relevant estimated coefficients are not statistically significant.

This study may guide universities in making important decisions about class time availabilities based on given student characteristics. Furthermore, the results of this study contribute to the literature on Economics Education by informing educational administrators about an important but understudied predictor of student performance and the academic benefits of offering more class sections in the morning. My finding is that productivity is higher in the morning than the afternoon, which can lead to increased academic performance. Universities can create efficiency gains by moving classes that are more affected by the time of day to the morning and moving other tasks and classes to the afternoon.

Literature Review

The literature shows that there are many factors that could affect student achievement and outcomes. Class time, school start time, class absence, and morningness-eveningness circadian performance could all affect student performance. A study by Besoluk, Onder, and Deveci (2011) sought to determine if different class start times affect student achievement by measuring final examinations given at different times. A total of 1471 university students between the ages of 18 and 25 years of age responded to a morningness-eveningness questionnaire, and data about their GPAs was collected from transcripts. Some of the students in the sample attended classes that started at 8:00 AM and ended at 2:00 PM. The remaining students followed the second schedule, which started at 3:00 PM and ended at 9:00 PM. The morningness-eveningness questionnaire scores were different by sex. These scores were somewhat able to predict academic success and student achievements according to class times. Final examinations also differed with respect to the time administered and the students' circadian preferences. Students who identified as having morning preference did indeed score higher on morning exams than those with intermediate or evening preference, showing that class start times and exam start times can actually impact academic performance. The authors maintain that morning classes can lead to higher achievement because of the unique nature of human beings, who organize their behavioral and biological activities based on a twenty-four hour period that has historically synchronized with light-dark cycles.

A study by Pope (2016) examined how time of day affects productivity, using a panel set of about two million students in Los Angeles, California. The research examined students' beliefs of time effects, class type and related these measures to GPA and state test scores. The author found that students learn more in the morning than they do later in the school day. Understanding that productivity is higher in the morning than the afternoon can allow for increased efficiency gains. By moving classes and tasks that are more advanced and affected by the time of day to the morning and moving other classes that are not as affected by time to the afternoon, performance can be improved. For instance, the study found that students who took a morning Math or English class, rather than afternoon, increased their GPA by 0.072 and 0.032, respectively.

The literature indicated that the effect of class start time differs between secondary education and college students. Cortes, Bricker, and Rohlfs (2010) also examined the effect that class time has on student achievement and outcomes for high school students in English and Mathematics. The authors used multivariate regressions to determine the effects of having English or math class during first period while controlling for other variables that could affect student development. According to the data, start times varied across the school district with times ranging from 6:40 AM until 9:08 AM. 91 percent of start times, however, were between 7:30 AM and 8:00 AM. The authors found that there were negative short and long term effects in school performance and tests when students took these classes early in the day. The authors note that the reasons for this could be due to general grogginess and the fact that there are more absences in first period than any other time of the day. Early start times could contribute to missed classes and late attendance, which can have negative consequences for students. Class absence also has the potential to affect student performance. A study by Arulampalam, Naylor, and Smith (2012) found that a causal relationship existed between missing class and having lower student performance. It is possible that the lower achievement of high school students in morning classes arises more from absences than the actual time of the class.

Some literature found the numerous studies about school start times insufficient. The school start time literature has indicated that due to changing sleep patterns during adolescence, student achievement can be improved by issuing later school times in order to account for less sleep and later circadian times. However, later start times are still relatively early in the morning, with most classes starting no later than 8:40AM. Dills and Hernadez-Julian (2008) found that students performed better in classes that meet later in the day. Additionally, Wahlstrom (2002) examined the effects of changes in a Minneapolis Public School from a 7:15 AM start time to an 8:40 AM start time and found positive effects across the board. While these two times are different, it did show that starting a little later in the day can be beneficial to students. The change led to a significant improvement in grades. Carrell et al (2011) studied the role of school start times at United States Air Force Academy by utilizing two policy changes in the daily schedule during a three year period. They found that starting the school day 50 minutes later increased overall academic achievement by about one-tenth of a standard deviation and that performance throughout the day was affected by early start times. A study by Edwards (2012) examined the effect of school start times. The author found that simply starting school an hour later can actually increase test scores by two percentage points, with the rationale being that teenagers have later Circadian cycles, thus allowing them to have extra sleep and therefore be well rested and have higher gains in learning. Studies by Carrel et al. (2011) and Dills and Hernandez-Julian, (2008) confirmed previous studies' findings. However, this says nothing about how teaching and learning ability changes throughout the day. While school start times have been shown to affect learning throughout the day, they do not affect differential learning, showing that the results of the school start time literature actually do measure slightly different effects.

Kokkelenberg, Dillon, and Christy (2008) determined that class size affects higher education students. They used an ordinal logit without fixed effects on over 760,000 undergraduate students. They found that larger class size typically correlated with a negative effect on student grades and performance. The authors controlled for student ability, peer effects, the academic department, minority status, level of course, and gender. This evidence concluded that student outcomes decrease as the class size increases. However, studies by Williams, Cook, Quinn and Jensen (1985), Pascarella and Terenzini (2005) determined that class size has very little effect on student achievement.

Several studies have examined how age and sex influence chronotype (Anderson 2008; Holmlund and Sund 2008; Husain and Millimet 2009; Fryer and Levitt 2010; and Lavy and Schlosser 2011). These studies discussed the gender differences according to morning-evening preferences among males and females. Morningness preference increased with age in adults. Furthermore, Adan and Natale (2002) found that women show a stronger inclination towards morningness than men in their rhythm expression. Other studies have concurred with Adam and Natale. A study by Roenneberg et al (2004) found that men scored higher in eveningness than females. It is important to note that social and cultural factors can contribute to discrepancies and differences in morningness-eveningness orientation (Borienskov et al, 2010). The study by Pope (2016) detailed that the effect of time of day was larger for males at a ten percent significance in two of four outcomes, such as Math GPA, Math test scores, English GPA, and English test scores.

Additionally, the literature has shown that female and male students perform differently in different areas of academia. Lumsden and Scott (1987) found that women tend to do more poorly than men on multiple-choice exams, while the reverse was true for essay questions. Research by Tay (1994) also found that gender was a factor that influenced student achievement and outcomes. The author used an ordinal probit model to estimate performance on an economics exam. The model assumed that several factors, including academic background, instructional input, intellectual ability, and personal factors affect a student's grade. One theory is that girls grow up in an environment that places value on achievement in areas other than businesses, thus slating them for a disadvantage in economics courses. It is important to note, though, that this research was done in Singapore, which does have different cultural expectations of women. Hernandez-Julian (2010) used a comprehensive administrative database from Clemson University to study the relationship between the incentives created by a South Carolina merit scholarship, LIFE, and students' academic performance. He hypothesized that being at risk of gaining or losing this scholarship would lead to increased effort and, as a result, higher grades. After controlling for student and course characteristics, his results suggested that the incentives created by the scholarship increased GPAs by 0.101 on a four-point scale. Moreover, his results indicated that for men, the relationship between the risk of gaining or losing the scholarship and grades was large and statistically significant, but for women there was little evidence linking the risk of gaining or losing the scholarship and grades. Cornwell, Mustard, and Van Parys (2013) showed that young girls displayed a more developed "attitude toward learning" and that teachers rewarded these attitudes by giving girls higher grades. In addition, Dynarski (2007) showed that females performed more strongly in both intensive preschool interventions early in education and in college later. The one agreement in all of the literature is that gender differences do occur in many aspects of education and achievement and across differing and compounding variables.

Empirical Methodology

I first divided the data into two groups: morning and afternoon. The first group includes any classes that begin from 8:00 A.M. to 11:30 AM. The second group includes any classes that began from 12:00 P.M. to 2:40 P.M. The study was restricted to on-campus classes, leaving out online classes. Second, I estimated the effect of class time on students' grades by using dummy variables for class times and by controlling for student characteristics and class characteristics. Third, I used ordinary least squares estimate to estimate the effect of class time on a student's grade.

I used a Bootstrapping method which allowed assigning measures of accuracy to sample estimates. This technique required the use of random sampling methods to calculate the standard errors. My procedures were resampling the dataset a given number of times, calculating a statistic from each sample, accumulating the results and calculating a sample distribution of the statistics.

To estimate the effect of class time on a student's grade, I used an education production function approach in which student performance is a function of student and class characteristics (Cortes, K. E., Bricker, J., and Rohlfs, C., 2010).

My OLS model was:

$$G_i = C + \beta' S_i + \delta' N_i + \gamma' studentcharacteristics_i + \delta' classcharacteristics_{\,i} + \varepsilon_i \quad (1)$$

The dependent variable is the letter grade in MICRO, on a four-point scale, where G_i is student i's grade on a scale from 0 to 4, with 0 representing a grade of F and 4 representing a grade of A. I also included plus and minus grades. For example, 3.33 represents a grade of B+ and 2.67 represents a grade of B-. S_i is a vector of class time dummy variables; N_i is the gender dummy variable. Student characteristics are:

$$studentcharacteristics_{\ i} = \gamma_1 Credit_i + \gamma_2 ACT.COMPOSITE_i + \gamma_3 ACT.MATH_i + \gamma_4 Age_i + \gamma_5 Race_i + \gamma_6 Maritalstatus_{\ i} (2)$$

where $credit_i$ represents the student's credit-hour load; $ACT.COMPOSITE_i$ represents the student's ACT composite score. $ACT.MATH_i$ represents the student's ACT math score. Class characteristics are as follows:

$$Classcharacteristics_i = \delta_1 Enroll_i + \delta_2 N_i + \delta_3\ Honor_i + \delta_4\ I_i + \delta_5\ SummerTerm_{\ i} (3)$$

where $Enroll_i$ represents the actual enrollment of the class that student i is enrolled in; N_i represents the number of times per week that student $i's$ class meets; I_i is the instructor fixed effect; $SummerTerm_{\ i}$ is a dummy variable that equaled 1 if the term is a summer; $Honor_i$ is a dummy variable that equaled 1 if the student is in an Honors class.

To control for differences in instructors' grading standards, I included instructor fixed effect. Many studies have determined that an instructor's overall effectiveness depends on instructor attributes, such as clarity of lectures, organization of course, the motivation given by the instructor, and success in building interpersonal connections with students. To examine the association between the attributes of economics instructors and the effectiveness of instruction, Jameson Boex (2000) used data from SEI questionnaires for instructors of economics at Georgia State University. Students self-reported the items, which included progress towards degree based on coursework, GPA on a 4.0 scale, whether or not the course was required for graduation, and the expected course grade. This was compared to an instructor questionnaire of 33 specific items about the instructor's manner of instruction, characteristics, and overall effectiveness and quality of the course. The results indicated that instructor characteristics influenced student performance based on their helpfulness and efficacy.

A student's grade in MICRO was also likely to be influenced by many factors related to that student's interest in the course subject and his or her level of economic intuition. These factors are likely related to how well the student performs in MICRO; hence, I included a dummy variable for academic major. Additionally, this control for student major ensured that selection bias did not occur. The literature suggests that the most talented females are not business majors, while male business majors may be a larger portion of the best male students on campus. Also, microeconomics is an option to fulfill requirements for General Education so that no class has business majors only. This study accounts for these confounding factors to highlight the differences in grades related to class time.

Ideally, the data set would also have information from the students' transcripts, including grades. However, the full transcript data were not available. This would have provided information about whether each student had fulfilled the calculus prerequisite or taken any other economics classes prior to taking MICRO, which would have helped further control for factors that may confound the estimated effect of class time on grades. This is important given the findings of Brasfield, McCoy, and Milkman (1992) and Raimondo, Esposito, and Gershenberg

(1990) who found a positive effect of math courses on performance in economics courses. Therefore, a simple comparison of the MICRO grades of students with enrollment in math classes could incur a serious selection bias. I controlled for this bias by including ACT MATH scores.

ACT composite scores were included in the regression as control variables. ACT composite score was a control for learning aptitude, effort, and discipline in academic work. Additionally, I used ACT composite scores to measure the link between higher achieving students and morning classes. Most similar studies (e.g., Siegfried and Fels, 1979) found SAT scores to be positively and significantly associated with test performance in principles courses. Hence, I included ACT composite in the regression.

Class size at the end of the semester was also used as a control variable in the regressions. Typically, no more than 45 students enroll in a section of MICRO. Of the 133 sections of MICRO, 56 had enrollments of 40 to 45 students, 17 had 74 to 90 students, 41 had 21 to 39 students, and six honors' classes had 17 to 20 students. Class size may be endogenous, and there might be a positive association between grade and class size. Students in smaller classes may do better because they receive more individual attention and may have better attendance. The literature confirms this association.

It is then necessary to examine the effect of morningness productivity and student achievement in terms of gender differences. To test for sex differences in effect size, I ran one model using a dummy for males to create an interaction term with all of the independent variables, so I estimated the marginal effect for each sex, and a t-test for a significant difference in marginal effects between the sexes. The literature shows that there are several gender differences in academia in terms of student achievement, outcome, and preferences. However, there are still a disproportionate number of men in economics relative to women. Although many sections of principles courses rely heavily on multiple-choice exams, table 1 shows that the mean female grade in MICRO is 2.49 while the mean male grade is 2.44.

Data

The ideal dataset includes information from multiple universities' official records regarding undergraduate students' age, gender, grades, credit load, and SAT/ACT scores, along with the class time of each class. However, no such data are freely available. I requested data from the Office of Institutional Effectiveness, Planning and Research at Middle Tennessee State University. The data cover a period of six years and include 5,803 individuals. The six-year range allowed me to accurately determine the effect of class time on students' grades. The data included students' gender, grade, age, race, grade point average (GPA), marital status, credit load, registration date, SAT/ACT scores, and major, along with whether the student is repeating the class after failing or withdrawing in a previous attempt. The data also included the class start times, enrollment, capacity, sessions per week, and instructor. To obtain the necessary control variables, I limited my sample to students taking principles of microeconomics (ECON 2420) from January 2009 through December 2014 at MTSU. A total of 5,803 students took 133 different MICRO classes in this time period. The sample consisted of 2,212 female and 3,591 male students, aged 16 to 45 years.

MICRO had eight to twelve different class start times each fall and spring semester, ranging from 8:00 A.M. until 6:00 P.M, providing plenty of variation in the variable of interest. Thirty-four different faculty members taught at least one section of MICRO during the period studied.

Table 1 summarizes student characteristics and class characteristics for both males and females. Student characteristics included the following: grades, ACT composite and math scores, credit load, full-time, age, marital status, and race (White, Black, Asian, or Hispanic). Class characteristics included the following: actual enrollment, number of meetings per week, maximum enrollment, term length, honors, and the instructor dummy variable. Table 1 shows that the mean male grade in MICRO is 2.44 while the mean female grade is 2.49. Of the males, 87.86% were full-time students compared to 86.35% of the females. The mean male ACT Composite score was 22.23 while the mean female ACT Composite score was 21.75. The mean male ACT Math score was 21.47 while the mean female ACT Math score was 20.61. The average male credit load was 13.21 credits while the average female credit load was 13.16 credits. The mean male age was 22.58 while the mean female age was 22.78. Of the male students, 70.51% were White, 17.13% were Black, 5.82% were Asian, and 3.26% were Hispanic. Of the female students, 65.78% were White, 20.80% were Black, 6.37% were Asian, and 3.25% were Hispanic. Marital status is also included with 78.78% of the male students being single, while 5.24% were married, 0.72% were divorced or separated. Among the female students 81.33% were single, while 6.19% were married, 2.17% were divorced or separated. The mean of the actual enrollment for male students was 54.38, while the mean of the actual enrollment for female students was 54.12. The ratio measure for excess capacity refers to the actual enrollment divided by the size of the class. The ratio measure was 84.7% for males, while it was 86.1% for female.

Table 2 summarizes the student characteristics and class characteristics for the males by class time. Out of the 3,591 males, 1,548 were in the morning classes, and 1,643 were in the afternoon classes. Table 2 shows lower student grades in the afternoon, with a mean of 2.31, while the mean grade received in the morning classes was 2.52. Among male students 89.47% were full-time in the morning classes compared to 89.77% for the afternoon classes. The mean male ACT Composite score was 22.31 in the morning classes, while the mean ACT Composite score was 22.13 for the afternoon classes. The mean male ACT Math score was 21.61 in the morning classes, while the mean ACT Math score was 21.30 for the afternoon classes. In the morning classes 71.58% of the male students were White compared to 68.90% for the afternoon classes. For Black students, 16.86% of the male students were in the morning classes and 18.38% in the afternoon classes. The mean Actual Enrollment for males was 46.92 for the morning classes, while it was 65.34 for the afternoon classes.

The ratio measure for excess capacity was 87% for the morning classes, while it was 85% for the afternoon classes. Of the students in the morning classes, 4.78% were married compared to 3.41% for the afternoon classes.

Table 2 summarizes the student characteristics and class characteristics for the females by class time. Of the 2,212 female students in the study, 911 were in the morning classes, 999 were in the afternoon classes. Table 2 shows lower student grades in the afternoon, with mean of 2.44, while the mean grades received in the morning classes were 2.54. Among the female students 89% were full-time in the morning classes compared to 91% for the afternoon classes. Of the female students in the morning classes, 4.94% were married compared to 4.50% for the afternoon classes. The mean female ACT Composite score was 21.76 in the morning classes, while the mean ACT Composite score was 21.78 for the afternoon classes. The mean female ACT Math score was 20.77 in the morning classes, while the mean ACT Math score was 20.55 for the afternoon classes. Of the female students, 65.86% in the morning classes were White compared to 65.37% for the afternoon classes. Black students made up 20.31% of the female students in the morning classes and 21.72% for the afternoon classes. The mean Actual Enrollment for females was 46.92 for the morning classes, while it was 65.55 for the afternoon classes. The ratio measure for excess capacity was 89% for females in the morning classes, while it was 87% for the afternoon classes.

Results

The results of equation (1) are shown in Table 3. The R square of 0.12 means that 12 percent of the variance was explained by the independent variables in the equation. The F statistic of 24 was significant at the 1 percent level.

The coefficient for the dummy variable Afternoon was the focus in this study. The finding of a significant positive coefficient indicates that Afternoon students outperformed morning students. However, a negative, significant coefficient would imply that the Afternoon students did not learn principles of microeconomics as well as the morning students. If the coefficient was not significant, the result rejects the hypothesis that course start time affects learning.

The dummy variable Afternoon has a negative, but not statistically significant coefficient. This implies that the Afternoon students may have the same knowledge as the morning students such that course time does not affect learning.

As expected, the coefficients for ACT Composite and ACT math were positive and significant, indicating a direct relationship between prior knowledge and general academic achievement with the measure of economics learning. The coefficient for the Term Credit Load variable was positive and significant, indicating that college class level does affect economics learning. The coefficient for Actual Enrollment was negative and significant, indicating that class size does affect students' grades. Students were negatively affected by large classes.

Robustness

In table 4 and 5, I ran one model by using a dummy for the male sex to create an interaction term with all of the independent variables by using a Bootstrapping method which allowed assigning measures of accuracy to sample estimates. I estimated separate marginal effects for each sex, and t-tests for significant marginal effects between the sexes.

Table 4 presents the results for male students. To gain further insight into the effect of class time on student performance I analyzed how a standard deviation would affect the performance of students. The coefficient for the Afternoon variable was negative and significant at the 10 percent level suggesting that a male student in an afternoon class could expect to earn a letter grade that is 0.029 GPA lower than he would have received in a morning class.

The most important independent variables are ACT math scores with a coefficient that was positive and significant at the 1 percent level and with highest standard deviation of 0.219. So an increase of the ACT math by one standard deviation would increase the male student's grade by 0.219 GPA points. Age had a negative coefficient that is significant at the 1 percent level. An increase in the Age of one standard deviation would decrease the male student's grade by 0.356 points GPA.

Table 5 presents the results for Female students. The coefficient for the Afternoon variable is positive but not significant. As the coefficient for the dummy variables Afternoon was the focus in this study, the insignificant findings indicate that female morning students do not outperform afternoon students. This result implies that Afternoon students did learn principles of microeconomics as well as the morning students.

For both males and female, the most important of the independent variables is ACT math with a coefficient variable that is positive and significant at the 1 percent level, and with the highest standard deviation of 0.126. So an increase of the ACT math by one standard deviation increased the female student's grade by 0.126 points GPA.

There was an inflation trend for grades from Spring 2009 to Fall 2014. The coefficient for the trend variable was positive and significant at the 5 percent level for male students but not significant for female students. One possible explanation is that students increased effort over time due to being at risk of gaining or losing a scholarship which will lead to higher grades. This was consistent with Hernandez-Julian's (2010) study also showing that student achievement increased with fear of losing merit scholarships, and this was more evident among men than women.

Conclusion

This paper studied the impact of class time on students' average grades. In a large sample of students who took MICRO from many different instructors at MTSU, a male student in an afternoon class could expect to earn a letter grade that is 0.029 GPA lower than he would have earned by taking the class in the morning. For females, the estimated coefficient is not statistically significant.

There are several explanations for why women and men might perform differently in classes that vary by the time of the day. Besoluk, Onder, and Deveci (2011) found that women are more inclined than men to prefer morning times. Also, Adan and Natale (2002) found that women show a stronger inclination towards morningness than men in their circadian rhythm expression.

Another possible explanation for different results between males and females is that females typically display a more developed attitude toward learning (Cornwell, Mustard, and Van Parys, 2013) and that teachers reward these attitudes by giving girls higher grades. In addition, Dynarski (2007) shows that there are large sex differences in educational outcomes as females respond more strongly to intensive school interventions than men. These results may raise questions of how to improve males' non-cognitive skills and create an alternative method of instruction to communicate more effectively to males who have different non-cognitive skill sets than females. After studying the impact of class time on average student grades, MTSU should offer more sections of microeconomics principles in the morning. As the results from my study show, students, especially males, who take microeconomics courses in the morning are likely to have higher levels of student achievement and more favorable academic outcomes. As male retention and graduation rates continue to decline to below those of their female counterparts, offering more morning sections of microeconomics principles would raise male comprehensive grade point averages, retention rates and graduation rates, therefore allowing MTSU to boost its overall student success rates.

REFERENCES

Adan, A., & Natale, V. (2002). Gender differences in morningness–eveningness preference. *Chronobiology International, 19*(4), 709-720.

Anderson, M. L. (2008). Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects. *Journal of the American Statistical Association, 103*(484), 1481-1495.

Arulampalam, W., Naylor, R. A., & Smith, J. (2012). Am I missing something? The effects of absence from class on student performance. *Economics of Education Review, 31*(4), 363-375.

Beşoluk, Ş., Önder, İ., & Deveci, İ. (2011). Morningness-eveningness preferences and academic achievement of university students. *Chronobiology International, 28*(2), 118-125.

Borisenkov, M. F., Perminova, E. V., & Kosova, A. L. (2010). Chronotype, sleep length, and school achievement of 11-to 23-year-old students in northern European Russia. *Chronobiology International, 27*(6), 1259-1270.

Brasfield, D., McCoy, J., & Milkman, M. (1992). The effect of university math on student performance in principles of economics. *Journal of Research and Development in Education, 25*(4), 240-247.

Cameron, S. V., & Heckman, J. J. (1993). The nonequivalence of high school equivalents. *Journal of Labor Economics, 11*(1, Part 1), 1-47.

Carrell, S. E., Maghakian, T., & West, J. E. (2011). A's from Zzzz's? The causal effect of school start time on the academic achievement of adolescents. *American Economic Journal: Economic Policy, 3*(3), 62-81.

Cornwell, C., Mustard, D. B., & Van Parys, J. (2013). Noncognitive skills and the gender disparities in test scores and teacher assessments: Evidence from primary school. *Journal of Human Resources, 48*(1), 236-264.

Cortes, K. E., Bricker, J., & Rohlfs, C. (2012). The role of specific subjects in education production functions: Evidence from morning classes in Chicago public high schools. *The BE Journal of Economic Analysis & Policy, 12*(1).

Currie, J., & Thomas, D. (1999). *Early test scores, socioeconomic status and future outcomes* (No. w6943). National bureau of economic research.

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

Dynarski, S. (2007). Cradle to college: The puzzle of gender differences in educational outcomes. (*Unpublished manuscript). Cambridge, MA: Harvard University*.

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

Fryer, R. G., & Levitt, S. D. (2010). An empirical analysis of the gender gap in mathematics. *American Economic Journal: Applied Economics, 2*(2), 210-240.

Goldin, C., Katz, L. F., & Kuziemko, I. (2006). The homecoming of American college women: The reversal of the college gender gap. *The Journal of Economic Perspectives, 20*(4), 133-133.

Hernández-Julián, R. (2010). Merit-based scholarships and student effort. *Education, 5*(1), 14-35.

Holmlund, H., & Sund, K. (2008). Is the gender gap in school performance affected by the sex of the teacher? *Labour Economics, 15*(1), 37-53.

Husain, M., & Millimet, D. L. (2009). The mythical 'boy crisis'? *Economics of Education Review, 28*(1), 38-48.

Jameson Boex, L. (2000). Attributes of effective economics instructors: An analysis of student evaluations. *The Journal of Economic Education, 31*(3), 211-227.

Kokkelenberg, E. C., Dillon, M., & Christy, S. M. (2008). The effects of class size on student grades at a public university. *Economics of Education Review, 27*(2), 221-233.

Lavy, V., & Schlosser, A. (2011). Mechanisms and impacts of gender peer effects at school. *American Economic Journal: Applied Economics, 3*(2), 1-33.

Lumsden, K. G., & Scott, A. (1987). The economics student reexamined: Male-female differences in comprehension. *The Journal of Economic Education, 18*(4), 365-375.

Melfi, C., & Waldman, D. M. (1987). Limited and discrete dependent variable models: Use, applications, and comparisons. *Econometric Modeling in Economic Education Research* (pp. 185-205). Dordrecht, Netherlands:Springer.

Murnane, R. J., Willett, J. B., & Levy, F. (1995). *The growing importance of cognitive skills in wage determination (No. w5076). National Bureau of Economic Research.*

Pascarella, E. T., & Terenzini, P. T. (2005). *How college affects students* (Vol. 2). San Francisco, CA: Jossey-Bass.

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

Raimondo, H. J., Esposito, L., & Gershenberg, I. (1990). Introductory class size and student performance in intermediate theory courses. *The Journal of Economic Education, 21*(4), 369-382.

Roenneberg, T., Wirz-Justice, A., & Merrow, M. (2003). Life between clocks: daily temporal patterns of human chronotypes. *Journal of Biological Rhythms, 18*(1), 80-90.

Siegfried, J. J., & Fels, R. (1979). Research on teaching college economics: A survey. *Journal of Economic Literature*, *17*(3), 923-969.

Tay, R. S. (1994). Students' Performance in Economics: Does the norm hold across cultural and institutional settings? *The Journal of Economic Education, 25*(4), 291-301.

Wahistrom, K. (2002). Changing times: Findings from the first longitudinal study of later high school start times. *Nassp Bulletin, 86*(633), 3-21.

Williams, D. D., Cook, P. F., Quinn, B., & Jensen, R. P. (1985). University class size: Is smaller better? *Research in Higher Education, 23*(3), 307-318.

APPENDICES

APPENDIX A: TABLES

Table 1.1 Descriptive Statistics: Student Characteristics and Class Characteristics for Male and Female

	Male			Female		
Variable	Observations	Mean	Std. Dev.	Observations	Mean	Std. Dev.
Student Characteristics						
Grades	3439	2.44	1.28	2098	2.49	1.27
ACT Composite	2716	22.23	3.76	1642	21.75	3.68
ACT Math	2716	21.47	4.13	1641	20.61	3.94
Credit load	3591	13.21	2.92	2212	13.16	3.14
Full-time Status	3591	87.86%	32.67%	2212	86.35%	34.34%
Cumulative GPA	3580	2.73	0.60	2206	2.89	0.59
Age	3591	22.58	4.56	2212	22.78	5.60
Race						
White	3591	70.51%	45.61%	2212	65.78%	47.46%
Black	3591	17.13%	37.68%	2212	20.80%	40.59%
Asian	3591	5.82%	23.42%	2212	6.37%	24.44%
Hispanic	3591	3.26%	17.76%	2212	3.25%	17.75%
Marital Status						
Single	3591	78.78%	40.89%	2212	81.33%	38.98%
Married	3591	5.24%	22.28%	2212	6.19%	24.11%
Divorced or Separated	3591	0.72%	8.48%	2212	2.17%	14.57%
Class Characteristics						
Actual Enrollment	3591	54.38	22.98	2212	54.12	23.04
Maximum Enrollment	3591	67.33	32.74	2212	65.47	31.57
Ratio measure for excess capacity	3591	84.7%	20%	2212	86.1%	19%
Number of section per semester	3591	9.58	2.18	2212	9.54	2.07
Number of day meeting	3591	2.32	0.68	2212	2.24	0.67
Full-Term	3591	94.99%	21.82%	2212	95.71%	20.28%
Honor	3591	1.56%	12.39%	2212	1.67%	12.83%

Notes:

Ratio measure for excess capacity = Actual Enrollment / size of the class

Data Source: Office of Institutional Effectiveness Planning at MTSU

Table 1.2 Descriptive Statistics: Student Characteristics and Class Characteristics for Male and Female by Course Time

	Male				Female			
	Morning		Afternoon		Morning		Afternoon	
	8:00 AM - 11:30 AM		12:00 PM - 2:40 PM		8:00 AM - 11:30 AM		12:00PM-2:40PM	
Variable								
Student Characteristics								
Grades	2.52	1.21	2.31	1.34	2.54	1.21	2.44	1.32
ACT Composite	22.31	3.77	22.13	3.74	21.76	3.78	21.78	3.56
ACT Math	21.61	4.12	21.30	4.10	20.77	4.07	20.55	3.81
Credit load	13.46	2.89	13.29	2.67	13.52	2.93	13.50	2.71
Full-time Status	89.47%	30.70%	89.77%	30.31%	89.79%	30.29%	91.09%	28.50%
Cumulative GPA	2.77	0.60	2.70	0.60	2.93	0.58	2.86	0.60
Age	22.29	4.45	22.25	3.85	22.15	4.74	22.14	4.88
Race								
White	71.58%	45.12%	68.90%	46.31%	65.86%	47.44%	65.37%	47.60%
Black	16.86%	37.45%	18.38%	38.74%	20.31%	40.25%	21.72%	41.26%
Asian	5.30%	22.40%	6.09%	23.92%	6.48%	24.62%	6.01%	23.77%
Hispanic	3.23%	17.69%	3.16%	17.51%	2.85%	16.66%	3.30%	17.88%
Marital Status								
Single	81.59%	38.77%	80.04%	39.98%	83.21%	37.40%	84.98%	35.74%
Married	4.78%	21.34%	3.41%	18.15%	4.94%	21.68%	4.50%	20.75%
Divorced or Separated	0.71%	8.40%	0.91%	9.51%	2.20%	14.66%	1.50%	12.17%
Class Characteristics								
Actual Enrollment	46.92	18.73	65.34	23.06	46.92	18.20	65.55	23.49
Maximum Enrollment	59.64	40.04	77.77	22.03	57.44	37.66	76.43	23.00
Ratio measure capacity	87%	20%	85%	19%	89%	18%	87%	18%
Section per semester	9.32	2.34	9.78	2.06	9.33	2.13	9.72	2.08
Number of day meeting	2.79	0.63	2.08	0.39	2.67	0.64	2.09	0.41
Full-Term	93.15%	25.26%	96.04%	19.50%	94.95%	21.91%	95.60%	20.53%
Honor	3.04%	17.16%	0.55%	7.38%	3.18%	17.57%	0.80%	8.92%
No. Observations	1548		1643		911		999	

Notes:

Ratio measure for excess capacity = Actual Enrollment / capacity

Data Source: Office of Institutional Effectiveness Planning at MTSU

Table 1.3 Ordinary Least Squares Model

Variable	Model			
	Coefficien	Standard Error	t value	Pr(>|t|)
Afternoon	-0.053	0.053	-1.000	0.318
Student Characteristics				
ACT Composite	0.031***	0.008	3.853	0.000
ACT Math	0.057***	0.007	7.810	0.000
Term Credit Load	0.051***	0.008	6.681	0.000
Age	-0.127**	0.042	-3.005	0.003
Race: Black	-0.218***	0.048	-4.513	0.000
Major: Accounting	0.184***	0.051	3.580	0.000
Major: Business	-0.134**	0.046	-2.913	0.004
Actual Enrollment	-0.003*	0.001	-2.179	0.029
Honor	0.405*	0.207	1.957	0.050
Summer Term	0.781***	0.128	6.080	0.000
Trend	0.009*	0.005	1.718	0.086
(Intercept)	0.000	0.018	0.000	1.000
R-squared	0.1288			
No. Observations	3591			
F-statistic:	42.77	P-value:	0.000	

Notes: Morning: 8:00 AM - 11:30 AM, Afternoon 12:00 PM - 2:40 PM
Student Characteristics: ACT Composite, ACT Math, Term Credit Load, Major, Age, Marital Status, Race: White, Black, Asian, and Hispanic. Class Characteristics: Actual Enrollment, Number of day meeting, Summer Term, Honor, and Instructor.
Standard errors are in parentheses; ***, **, and * indicate statistical significance at 1, 5 and 10 percent levels. The dependent variable is the letter grade in MICRO, on a scale from 0 to 4. Data Source: Office of Institutional Effectiveness Planning at MTSU

Table 1.4 Testing for Gender Differences - Males

Variable	Coefficient	Model Standard Coefficient	Standard Error	P-Value
Afternoon	-0.096*	-0.029	(0.067)	0.077
ACT Composite	0.021**	0.061	(0.011)	0.027
ACT Math	0.067***	0.219	(0.010)	0.000
Term Credit Load	0.059***	0.124	(0.010)	0.000
Age	-0.177***	-0.356	(0.070)	0.006
Race: Black	-0.178***	-0.055	(0.058)	0.001
Major: Accounting	0.271***	0.069	(0.070)	0.000
Major: Business	-0.122**	-0.039	(0.057)	0.015
Major: Political Science	-0.097	-0.013	(0.144)	0.251
Class Characteristics Actual Enrollment	-0.003**	-0.045	(0.002)	0.030
Honor	0.489***	0.036	(0.204)	0.008
Summer Term	0.942***	0.128	(0.144)	0.000
Trend	0.011**	0.030	(0.006)	0.044

Notes: Morning: 8:00 AM - 11:30 AM, Afternoon 12:00 PM - 2:40 PM
Student Characteristics: ACT Composite, ACT Math, Term Credit Load, Major, Age, Marital Status, Race: White, Black, Asian, and Hispanic.
Class Characteristics: Actual Enrollment, Number of day meeting, Summer Term, Honor, and Instructor. Standard errors are in parentheses; ***, **, and * indicate statistical significance at 1, 5 and 10 percent levels. The dependent variable is the letter grade in MICRO, on a scale from 0 to 4. Data Source: Office of Institutional Effectiveness Planning at MTSU

Table 1.4 Testing for Gender Differences - Females

Variable	Coefficient	Model Standard Coefficient	Standard Error	P-Value
Afternoon	0.043	0.013	(0.087)	0.311
Student Characteristics				
ACT Composite	0.049***	0.142	(0.015)	0.001
ACT Math	0.041***	0.126	(0.014)	0.001
Term Credit Load	0.031***	0.065	(0.013)	0.008
Age	-0.089*	-0.193	(0.074)	0.117
Race: Black	-0.259***	-0.085	(0.072)	0.000
Major: Accounting	0.105*	0.034	(0.074)	0.078
Major: Business	-0.148**	-0.047	(0.078)	0.029
Major: Political Science	-0.353*	-0.042	(0.227)	0.060
Class Characteristics				
Actual Enrollment	-0.003	-0.036	(0.002)	0.122
Honor	0.228	0.016	(0.315)	0.234
Summer Term	0.410**	0.056	(0.224)	0.034
Trend	0.007	0.021	(0.008)	0.188

Notes: Morning: 8:00 AM - 11:30 AM, Afternoon 12:00 PM - 2:40 PM
Student Characteristics: ACT Composite, ACT Math, Term Credit Load, Major, Age, Marital Status, Race: White, Black, Asian, and Hispanic.
Class Characteristics: Actual Enrollment, Number of day meeting, Summer Term, Honor, and Instructor. Standard errors are in parentheses; ***, **, and * indicate statistical significance at 1, 5 and 10 percent levels. The dependent variable is the letter grade in MICRO, on a scale from 0 to 4. Data Source: Office of Institutional Effectiveness Planning at MTSU

CHAPTER II: DOES MEETING ONCE A WEEK HARM STUDENTS' GRADES? A COMPARISON OF OUTCOMES IN ECONOMICS CLASSES

Introduction

Understanding course scheduling is imperative to university administrators responsible for scheduling decisions, faculty members who teach different course schedules and sections, and students planning their course schedules. This article estimates the effect of course schedule formats, such as weekly meeting frequency and term length, on a student's grade. I hypothesize that more frequent meetings per week will increase student outcomes. This study identifies effects that can inform pedagogical improvements for compressed terms and course scheduling.

Understanding strategies to increase student retention and achievement is imperative. If individual welfare falls with tuition increases (Krishna, and Tarasov, 2016), then when tuition rises, students need more reason to attend universities. Maintaining or increasing prestige, student retention, and graduation rates is very important to administrators striving to keep up enrollment in institutions of higher learning. It is also economically sound to encourage student retention, as it is more cost effective for administrators to ensure that current students' needs are met than to recruit new students.

This research will also benefit students who seek more effective ways to learn. Students who control their own learning are more successful, have greater motivation, and have higher education outcomes (Reeve, 2013). Understanding how the frequency of class meetings affects student achievement can help students control their own learning. Students will be better able to make sound scheduling decisions to foster student achievement and learning (Lai and Hwang, 2016).

The impact of education is an important topic for economists. Globalization and international trade require countries and their respective economies to compete. Successful countries hold competitive and comparative advantages over other countries. A major factor in the success of a country's economy is education (Bhorat, Cassim, and Tseng, 2016). The study of the economics of training and education involves effects on both employers and workers (Blundell et al, 1999). Two major concepts that influence the wage rate are training and education. Because education is such an important factor for the workforce and a country's economy, it is beneficial to determine the most efficient and effective ways to educate students and to increase student learning, achievement, and retention in order to produce skilled workers. Consequently, it is important to determine the effect of course scheduling, including the frequency of class sessions, on student achievement and outcomes.

To anticipate scheduling effects, it is helpful to review prominent educational concepts that may apply. One such concept is Spaced Versus Massed Practice. This common educational concept holds that spaced practice is overall more effective than massed practice. In other words, individuals realize increased learning when classes meet more frequently, even when actual instruction time is constant (Dunn and Hooks, 2015).

I analyze data from the Office of Institutional Effectiveness, Planning, and Research (IEPR) at Middle Tennessee State University (MTSU). The sample contains data for 5803 students who took MICRO from multiple instructors at MTSU. I present ordinary least squares estimates (OLS) for course schedule formats weekly meeting frequency and for term length effects.

I find that a student could expect to earn a grade point average (GPA) that is 0.245 points lower on a four point scale in a course meeting once per week relative to a course meeting three times per week. For a course meeting twice per week, a student could expect to earn a GPA that is statistically indistinguishable from that in a course meeting three times per week. Thus, meeting more times a week may lead to higher student achievement. Also, I find that term length does not make a significant difference in student grades.

Literature Review

The Spaced Versus Massed Practice theory helps to explain why more class times per week can improve earned grades among college students. The theory states that increased learning occurs when classes meet more, rather than fewer, times per week. This holds true even if the actual amount of instruction time is the same. Learning occurs more efficiently when more instruction sections occur in a shorter duration with time gaps in between (Dunn and Hooks, 2015). A class that meets two or three times per week for a total of three hours (spaced practice), is more efficient than a single session per week (massed practice). Many studies support the existence of the spacing effect including, Foma (1983), Krug, Davis, and Glover (1990), and Donovan and Radosevich (1999). Dempster (1989) determined that spaced repetitions, regardless of form, are a highly effective means of promoting learning. Hopkins et al (2015) found that spaced content was better than massed content in terms of increased student learning, as well as knowledge acquisition.

A study by Vernick, Reardon and Sampson (2004) determined that courses are most effective when meeting times are more frequent than once a week. This avoids overexposure to course activities and materials, therefore fostering student learning without overwhelming the students. This study was extended by Reardon, Leirer and Lee (2014), who hypothesized that course schedule formats, weekly meeting frequency, and term length could make a difference in student learning and evaluation of teaching. The authors examined 57 course sections over six years with four different class schedule formats. The content, structure of the class, and instructional methods remained the same among all classes, regardless of the section. The 16-week semester formats included classes that met once a week for three hours on Wednesdays; twice a week on Tuesdays and Thursdays; or three times a week for one hour on Monday, Wednesday and Friday. A fourth schedule option was a six week term in which classes met four times weekly for a total of eight hours per week, Monday through Thursday. The authors found that students had the lowest earned grades in sections that met once a week over sixteen weeks while students in the Monday to Thursday class section had significantly higher earned grades than all other formats. This suggests that more time spent in class per week increases student achievement.

Numerous studies of information processing theory and the spacing effect on learning have produced mixed findings. Gallo and Odu (2009) focused on assessing the relationship of course scheduling with student outcomes in Intermediate Algebra, the prerequisite course for College Algebra. The authors found no support for the idea that class scheduling can predict or improve student outcomes in developmental math. The authors recommended offering a variety of class scheduling options, because that would have no negative effect on student outcomes in Intermediate Algebra.

Only a few studies focus on class scheduling in business courses. Henebry (1997) studied the impact of class schedule on students enrolled in a financial management course and found higher pass rates and lower drop rates for classes meeting two or three times per week as compared to classes meeting only once per week. These findings are consistent with the spacing effect theory and with Gallo and Odu (2009).

In economic education, there is limited research on the relationship between course length, time, and student learning (Van Scyoc, 1993). Van Scyoc and Gleason (1993) compared a 14-week to a 3-week course in microeconomics. The authors determined that students in the compressed courses learned and retained at least as much knowledge as students in the traditional length courses.

However, Petrowsky (1996), who examined compressed macroeconomic principles courses, found diminished academic performance in those areas that stress comprehension and analysis over mere recall. Petrowsky found that summer students (compressed schedule) outperformed the spring students (traditional schedule) on tests from the first half of the course which involved simple recall of information. However, the summer students actually performed worse on the tests in the second half of course which involved comprehension, application, and analysis. Petrowsky recommended abandoning the two week format for economics classes, because compressed schedules were not good for courses which required more comprehension and analysis. One reason for this discrepancy between student learning outcomes in Micro and Macro courses could be that Macro is more difficult and advanced than Micro.

Economics may not be the best subject area for extremely accelerated classes. Essentially, even though the compressed courses did meet many times per week, they were too short for students to comprehend complex economic content. Meeting more times a week over a traditional semester may lead to better outcomes in terms of comprehension and analysis.

Logan and Geltner (2000) sought to determine the relationship between compressed courses and student success. A total of 414,076 student enrollments in term lengths of 6, 8, and 16 weeks were studied, covering the period between fall 1998 and winter 2001. Overall, the study found that classes that met more often could potentially be better for student learning.

There have been conflicting results on the impact of class scheduling on student performance in accounting courses. While a great deal of research supports the notion that spaced practice is more efficient and leads to increased student learning, Carrington (2010) found that night students in Intermediate Accounting with longer, but less frequent sessions performed significantly better than students meeting three times a week in fifty minute sessions. The author claims that the material might have been too complex to be effectively taught in fifty minute class sessions, such that longer sections were necessary in order to properly present the course material. Another possibility was that the longer break between class sessions allowed students more time to study material outside of the classroom. This contradicts the theory of distributed practice that has widely been accepted by cognitive and educational psychologists. However, it offers an interesting viewpoint on complexity of course content in relation to frequency and duration of class sessions. These results are consistent with studies by Daniel (2000) and Scott and Conrad (1991).

Research suggests that student learning is more pronounced in a course that meets several times a week over many weeks, such as in a traditional-length semester, rather than in a compressed course that lasts only a few weeks or meets only one time per week (Brookes 1985; Kirby-Smith 1987; Brett 1996; Scott 1996; Seamon, 2004). However, studies in educational psychology have produced mixed results that are not always consistent with the Spacing Effect.

A meta-analysis by Daniel (2000) found that compressed courses (courses that have a very short duration but meet more frequently during the week), resulted in equal or better student outcomes than traditional semester-long courses that met less frequently during the course of the week. Likewise, Scott and Conrad (1991) reviewed the literature on traditionally scheduled courses, summer courses, interim summer courses, and weekend and night classes. The authors concluded that compressed courses were equal or better than traditional courses in terms of student outcomes.

Empirical Strategy

I hypothesize that weekly meeting frequency and term length make a difference in student learning. This study of six years of microeconomics principles courses examines the effect of three different class schedule formats on student’s grades. Also, it examines the effect of term lengths (3 weeks, 5 weeks, 14 weeks) on students' grades.

My study design can be summarized as follows. First, I estimate the effect of course schedule weekly meeting frequency on students' grades in 118 course sections over six years with three different class schedule formats, controlling for student characteristics and class characteristics. The formats in a 14-week semester include meeting once a week for three hours on Thursday; twice a week on Tuesdays and Thursdays; twice a week on Monday and Wednesday; or three times a week for one hour on Monday, Wednesday and Friday.

Second, I estimate the effect of the term lengths (3 weeks, 5 weeks, 14 weeks) on students' grades by controlling for student characteristics and class characteristics. Of the 118 sections of Micro principles classes, 103 sections were taught during a regular 14-week semester, four sections were taught in a 3-week interim, and 11 sections were taught in a 5-week interim. The 3-week course was offered in the month of May and was part of the summer semester. The 5-week course was offered in the month of June or July and was part of the summer semester. The cost of the 3-week and 5-week courses was the same as the cost of the 14-week course, and the course requirements were the same.

The first hypothesis is tested by Model 1, which estimates the effect of course schedule formats weekly meeting frequency on a student's grade in principles of microeconomics classes. I use an education production function approach in which student performance is a function of student and class characteristics (Cortes, K. E., Bricker, J., and Rohlfs, C., 2010).

My OLS model is:

$$\begin{aligned} GRADE_i = C + \beta\ 'MEETING_i \\ + \gamma\ 'studentcharacteristics(\gamma_1\, credit_{\,i} + \gamma_2\, ACT_{\,i} + \gamma_3 AGE_{\,i} + \gamma_4 Race_i \\ + \gamma_{\,5} Maritalstatus_i + \gamma_6 GENDER_i) \\ + \delta\ 'classcharacteristics(\delta_1 Size_i + \delta_2\, I_i) + \beta\ 'TIME_i + \varepsilon_i \ (1) \end{aligned}$$

The dependent variable is the letter grade in MICRO at the end of the term, measured on a 4-point scale, where GRADE $_i$ is student i's grade on a scale from 0 to 4, with 0 representing a grade of F and 4 representing a grade of A. I also included plus and minus grades. For example, 3.33 represents a grade of B+ and 2.67 represents a grade of B-. MEETING $_i$ is a vector of the course schedule weekly meeting dummy variables. The coefficients for the dummy variables $MEETING$ one time and $MEETING$ two-time are the focus in this model. The finding of a significant negative coefficient would indicate that students in classes meeting three times a week outperformed those in classes meeting one and two times a week.

$GENDER_i$ is a gender dummy variable that equals 1 if the student is a male; credit i represents the student's credit hours load; $ACT\ _i$ represents the student's ACT score; AGE $_i$ is the age of the student; Size $_i$ represents the class size of the class that student i is enrolled in; I_i is the vector of instructor fixed effect; and $TIME\ _i$ is a vector of time of day dummy variables.

The second hypothesis is tested by Model 2, which measures the effect of semester length on students' grades in principles of microeconomics classes. The model is represented by the following equation:

$$\begin{aligned} GRADE_i = C + \beta\ '\text{LENGTH}\ _i \\ + \gamma\ 'studentcharacteristics(\gamma_1\ credit\ _i + \gamma_2\ ACT\ _i + \gamma_3 AGE\ _i + \gamma_4 Race_i \\ + \gamma\ _5 Maritalstatus_i + \gamma_6 GENDER_i) \\ + \delta\ 'classcharacteristics(\ \delta_1 Size_i + \delta_2\ I_i) + \beta\ 'TIME_i + \varepsilon_i\ (1) \end{aligned}$$

The dependent variable is the letter grade in MICRO at the end of the term. LENGTH $_i$ is a vector of the term length dummy variables. The coefficients for the dummy variables $LENGTH$ 3 weeks and $LENGTH$ 5 weeks are the focus in this model. The finding of a significant negative coefficient would indicate that students in 14-week classes outperformed those in 3-week and 5-week classes. All the other variables are the same as in model one.

All of the principles classes started at different times of the day. The 3-week, 5-week, and the 14-week courses were not scheduled at the same time. Thus, I controlled for that by adding meeting time dummy variables. The 14-week classes met twice a week for one and one-half hours, once a week for three hours, or three times a week for one hour. In contrast, the 3-week classes met five times a week for three hours each day, and the 5-week classes met four times a week for two hours each day.

Data

The data were obtained from the Office of Institutional Effectiveness, Planning and Research at Middle Tennessee State University. The data cover a period of six years from January 2009 through December 2014 for 5,803 individuals. The data include information on students' gender, grade, age, race, grade point average (GPA), marital status, credit load, and ACT scores.

The data also include information on class times, enrollment, capacity, course schedule formats, weekly meeting frequency, term length, and instructor. A total of 5,803 students took 133 different Principles of Microeconomics (ECON 2420) classes in this time period, with the sample consisting of 2,212 female and 3,591 male students, aged 16 to 45 years. Thirty-four different faculty members taught at least one section of MICRO during the period studied. The variation in grading standards among instructors is controlled for using instructor fixed effects.

Table 1 presents student characteristics and class characteristics. Student characteristics include gender, age, marital status, grades, ACT composite and math scores, credit load, full-time status, and race. Course characteristics include actual enrollment, the number of times the class met per week, maximum enrollment, the term length, honors status, and the instructor dummy variable. Sixty-one percent of the students were male and 39% were female. The mean for student grades was 2.46. The mean ACT Math score was 21.14. The average credit load was

13.19 credits. 87.28% of students were enrolled full time. The mean age was 22.65. 68.71% of students were White, while 18.52% were Black, 6.03% were Asian, and 3.26% were Hispanic. 79.75% of the students were single, while 5.60% were married, 1.28% were divorced or separated. The mean of the actual enrollment was 54.28. The mean of maximum enrollment was 66.62. 6.29% of course sections met once a week, 63.90% met twice a week, and 25.31% met three times a week.

Table 2 analyzes the descriptive statistics of student characteristics and class characteristics by meeting times per week. Students who met once a week had a mean grade of 2.49, while students who met two times had a mean grade of 2.45, and students who met three times had a mean grade of 2.38. The ACT Math score was relatively similar across class meetings; students in courses meeting one time a week had a mean score of 21.19, students meeting twice a week had a mean score of 21.10, and students meeting three times a week had a mean score of 21.39. The mean age of the class meeting once a week was 27.94 compared to a mean age of 22.26 in courses that met two times a week and a mean age of 22.10 in courses that met three times a week.

Marital status varied by the number of times classes met per week. In classes that students met once a week, 56.16% of students were single, and 20.55% were married. In classes meeting twice a week, 82.06 % of students were single and 4.42% were married. In courses meeting three times a week, 83.59% were single and 4.5% were married. Student credit loads varied by meeting time per week, with students who met once a week having an average course load of 10.25 hours, students who met twice had a mean credit load of 13.64, and students who met three times had a mean credit load of 13.73. 54.25% of students meeting once a week were enrolled full time, whereas 92.58% of students meeting twice a week were full time, and 93.53% of students meeting three times a week were full-time. 54% of students were male in classes that met once a week, 60% were male in classes that met twice a week, and 65% were male in classes that met three times a week. Mean enrollment for once-a-week classes was 35.78, 58.84 for twice a week, and 53.70 for three times a week. 100% of classes meeting once a week met in the evening, starting between 4:10 PM and 6:00 PM. 23% of the twice a week classes met in the morning, starting between 8:00 AM and 11:30 AM, 68% met in the afternoon, starting between noon and 2:40 PM. 100% of the three times a week courses met in the morning, 8:00 AM until 11:30 AM.

Results

Table 3 presents the Fixed-effects (within) Regression Model for the frequency of meetings per week. The F statistic rejects the hypothesis that the coefficients on the regressors are all jointly zero. So my model is significant. The results of Model 1 are based on the specification that controls for class characteristics. The estimated coefficients on class meeting frequency are negative but not statistically significant.

The results of Model 2 are based on the specification that controls for student characteristics and class characteristics. The estimated coefficients are negative and statistically significant at the 5 percent level: a student could expect to earn a letter grade that is 0.244 lower in a class meeting once a week relative to a class meeting three times a week. These results show that meeting more times a week is associated with increased student achievement.

Table 4 presents the results for the ordinary least squares (OLS) regression for the term length. The results of Model 1 and Model 2 show the estimated coefficients are negative but not statistically significant. The dummy variables' coefficients for course length, 3 WEEKS and 5 WEEKS, were not statistically significant. This finding shows that students taking the 3-week and 5-week courses retained knowledge from principles of microeconomics as well as the 14-week students did. These results suggest that term length does not make a difference in student learning.

I found that sections that met once a week over 14 weeks had the lowest earned grades. The Monday, Wednesday and Friday class sections had significantly higher earned grades than all other formats, suggesting that more time spent per week in class has a direct impact on increased student achievement.

Conclusion

Based on the literature, I hypothesized that students would have better learning outcomes and higher student achievement when participating in courses scheduled over longer time periods and in classes that met more frequently during the week. My results show that meeting more times a week over a traditional semester may lead to higher success and student achievement but term length does not make a significant difference.

While some studies found that classes meeting for longer periods of time but less frequently were successful, the vast majority of peer-reviewed empirical research suggests that the spaced effect theory is more accurate in terms of how the brain works and is a better means of achieving higher student learning and outcomes. Understanding spaced versus massed theory can give us a better understanding of how course scheduling in academia can prioritize student learning by scheduling according to the latest cognitive research on how students think and learn.

There are limitations as some of the literature determined that difficult or complex subjects might benefit from longer class periods that meet less frequently. This is because difficult course subjects might need longer than the standard 50 minute format for most class sections that meet three times per week (Carrington, 2010). There are very few studies that address the Spaced Versus Massed Practice theory in the application of college-level economics. Future research should seek to determine if the spaced method is more effective than massed practice method in Economic sections at both the undergraduate and graduate levels.

Previous studies (Reardon, Leirer, and Lee, 2014) on course scheduling have limitations. They aggregated class section scores instead of individual student scores. Also, participants were undergraduates taking a career planning course. I attempted to address these issues by using individual student scores for principles of economics classes.

My results are for only one university’s Microeconomics course. Caution should be exercised when generalizing these results to other courses, especially outside of the field of Economics. The ideal data set should include information from multiple universities’ official records regarding undergraduate students’ age, gender, grades, credit load, and ACT scores. However, no such data are freely available.

Choosing one course to study could reduce the possibility of course differences. I chose principle of microeconomics. Because of this, the content, structure of the class, and instructional methods remained the same among all classes, regardless of the section.

The results of this study suggest that the length of a course does not affect students' grades in microeconomics. This supports the conclusions of earlier research that students in short-term courses perform as well as students taking the same courses in a traditional semester-length format. Thus, this research recommends continuing the three-week and five-weeks format summer classes for microeconomics principles. However, Petrowsky (1996) recommends abandoning the two-week term for macroeconomics principles, finding compressed courses were not good for subjects that required more comprehension and analysis. Hence, Economics may not be the best subject area for extremely accelerated classes. This is likely because more advanced courses, such as Macroeconomics, require deeper explanation and cannot be compressed into a shorter time period. Thus, more research should be done in order to determine if compressed courses have a negative impact on student outcomes and learning.

The present study may help to guide universities in making important decisions about meeting times to offer based on given student characteristics. Hence, the results of this study recommend scheduling courses that meet more times a week in order to increase student success. Also, the results of this study support continuing the three-week and the five-week format summer classes for microeconomics principles classes.

REFERENCES

Bhorat, H., Cassim, A., & Tseng, D. (2016). Higher education, employment and economic growth: Exploring the interactions. *Development Southern Africa, 33*(3), 312-327.

Blundell, R., Dearden, L., Meghir, C., & Sianesi, B. (1999). Human capital investment: the returns from education and training to the individual, the firm and the economy. *Fiscal Studies, 20*(1), 1-23.

Brett, M. (1996). Teaching extended class periods. *Social Education, 60*, 77-79.

Brookes, M. C. (1985). Time in Learning: Does distribution make a difference? *Community/Junior College Quarterly of Research and Practice, 9*(3), 291-296.

Carrington, L. G. (2010). The impact of course scheduling on student success in intermediate accounting. *American Journal of Business Education, 3*(4), 51.

Caskey, S. R. (1994). Learning outcomes in intensive courses. *The Journal of Continuing Higher Education, 42*(2), 23-27.

Cortes, K. E., Bricker, J., & Rohlfs, C. (2012). The role of specific subjects in education production functions: Evidence from morning classes in Chicago public high schools. *The BE Journal of Economic Analysis & Policy, 12*(1).

Daniel, E. L. (2000). A review of time-shortened courses across disciplines. *College Student Journal, 34*(2).

Dempster, F. N. (1988). The spacing effect: A case study in the failure to apply the results of psychological research. *American Psychologist, 43*(8), 627.

Donovan, J. J., & Radosevich, D. J. (1999). A meta-analytic review of the distribution of practice effect: Now you see it, now you don't. *Journal Of Applied Psychology, 5*, 795.

Dunn, K., & Hooks, K. (2015). Course scheduling and student learning: An empirical investigation. *Global Perspectives on Accounting Education, 12*, 73-95.

Fike, D. S., & Fike, R. (2013). A multilevel analysis of the association of class schedule with student outcomes in community college developmental math. *Community College Journal of Research and Practice, 37*(11), 816-827.

Foma, E. (1983). Word processing text-editing massed versus spaced practice. *Journal of Studies in Technical Careers, 5*(1), 19-26.

Gallo, M. A., & Odu, M. (2009). Examining the relationship between class scheduling and student achievement in college algebra. *Community College Review, 36*(4), 299-325.

Henebry, K. (1997). The impact of class schedule on student performance in a financial management course. *Journal of Education for Business, 73*(2), 114-120.

Hopkins, R. F., Lyle, K. B., Hieb, J. L., & Ralston, P. A. (2016). Spaced retrieval practice increases college students' short-and long-term retention of mathematics knowledge. *Educational Psychology Review, 28*(4), 853-873.

Kirby-Smith, J. (1987). Effects of intensive college courses on student cognitive achievement, academic standards, student attitudes, and faculty attitudes. *Unpublished doctoral dissertation, University of Southern California*.

Krishna, K., & Tarasov, A. (2016). Affirmative action: One size does not fit all. *American Economic Journal: Microeconomics, 8*(2), 215-252.

Krug, D., Davis, T. B., & Glover, J. A. (1990). Massed versus distributed repeated reading: A case of forgetting helping recall? *Journal of Educational Psychology, 82*(2), 366.

Lai, C.-L., & Hwang, G.-J. (2016). A self-regulated flipped classroom approach to improving students' learning performance in a mathematics course. *Computers & Education, 100*, 126-140.

Logan, R., & Geltner, P. (2000). The influence of session length on student success. *Report for Santa Monica College*.

Petrowsky, M. C. (1996). The two week summer macroeconomics course: Success or failure? (Report No. 396779). Retrieved from ERIC

Reardon, R. C., Leierer, S. J., & Lee, D. (2014). Class meeting schedules in relation to students' grades and evaluations of teaching. *Professional Counselor, 2*(1), 81-89.

Reeve, J. (2013). How students create motivationally supportive learning environments for themselves: The concept of agentic engagement. *Journal of Educational Psychology, 105*(3), 579.

Scott, P. A. (1996). Attributes of high-quality intensive course learning experiences: Student voices and experiences. *College Student Journal, 30*, 69-77.

Scott, P. A., & Conrad, C. F. (1991). A critique of intensive courses and an agenda for research. (serial online), Available from: ERIC.

Seamon, M. (2004). Short-and long-term differences in instructional effectiveness between intensive and semester-length courses. *Teachers College Record, 106*(4), 635-650.

Van Scyoc, L. J., & Gleason, J. (1993). Traditional or intensive course lengths? A comparison of outcomes in economics learning. *The Journal of Economic Education, 24*(1), 15-22.

Vernick, S. H., Reardon, R. C., & Sampson Jr, J. P. (2004). Process evaluation of a career course: A replication and extension. *Journal of Career Development, 30*(3), 201-213.

APPENDICES

APPENDIX A: TABLES

Table 2.1 Descriptive Statistics: Student Characteristics and Class Characteristics

Variable	Observations	Mean	Std. Dev.
Student Characteristics			
Grades	5537	2.46	1.28
ACT Composite	4358	22.05	3.74
ACT Math	4357	21.14	4.08
Credit load	5803	13.19	3.01
Full-time Status	5803	87.28%	33.32%
Cumulative GPA	5786	2.79	0.60
Age	5803	22.65	4.99
Race			
White	5803	68.71%	46.37%
Black	5803	18.52%	38.85%
Asian	5803	6.03%	23.81%
Hispanic	5803	3.26%	17.75%
Marital Status			
Single	5803	79.75%	40.19%
Married	5803	5.60%	23.00%
Divorced or Separated	5803	1.28%	11.22%
Male	3591	61%	48%
Class Characteristics			
Actual Enrollment	5803	54.28	23.00
Maximum Enrollment	5803	66.62	32.31
Ratio measure for excess capacity	5803	85.3%	19%
Number of section per semester	5803	9.56	2.14
Full-Term	5803	95.26%	21.25%
Honor	5803	1.60%	12.56%
Meeting Per Week			
One time	5803	6.29%	24.28%
Two times	5803	63.90%	48.03%
Three times	5803	25.31%	43.49%

Table 2.2 Descriptive Statistics: Student Characteristics and Class Characteristics by Meeting Time Per Week.

	Meeting Time Per Week					
	One time		Two times		Three times	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Student Characteristics						
Grades	2.49	1.35	2.45	1.29	2.38	1.25
ACT Composite	22.24	3.82	22.03	3.75	22.14	3.70
ACT Math	21.19	4.35	21.10	4.06	21.39	4.07
Credit load	10.25	4.02	13.64	2.49	13.73	2.31
Full-time Status	54.25%	49.89%	92.58%	26.21%	93.53%	24.60%
Cumulative GPA	2.75	0.59	2.80	0.60	2.77	0.60
Age	27.94	7.88	22.26	4.40	22.10	4.51
Race						
White	76.99%	42.15%	67.72%	46.76%	68.48%	46.47%
Black	12.33%	32.92%	19.23%	39.42%	18.99%	39.24%
Asian	5.75%	23.32%	5.93%	23.63%	6.06%	23.86%
Hispanic	3.29%	17.86%	3.29%	17.84%	3.27%	17.78%
Marital Status						
Single	56.16%	49.69%	82.07%	38.37%	83.59%	37.05%
Married	20.55%	40.46%	4.42%	20.56%	4.15%	19.96%
Divorced or Separated	1.64%	12.73%	1.16%	10.71%	1.43%	11.87%
Male	54%	49%	60%	48%	65%	47%
Class Characteristics						
Actual Enrollment	35.78	10.30	58.84	22.72	53.70	19.85
Maximum Enrollment	52.83	21.78	68.46	24.85	72.48	45.44
Ratio measure for excess capacity	73%	18%	88%	18%	83%	21%
Number of section per semester	9.68	1.57	10.00	1.58	9.65	1.52
Full-Term	100%	0%	99.62%	6.13%	100.00%	0.00%
Honor	0%	0%	1.86%	13.52%	1.63%	12.68%
Time of meeting						
Morning 8:00 AM - 11:30 AM	0%	0%	23%	42%	100%	0%
Afternoon 12:00 PM - 2:40 PM	0%	0%	68%	47%	0%	0%
Evening 4:10 PM - 6:00 PM	100%	0%	9%	29%	0%	0%
No. Observations	365		3708		1469	

Table 2.3 Fixed-Effects (Within) Regression Model for Student Grades for Course Weekly Meeting Frequency

Variable	Model 1	Model 2
Meeting one time	-0.09142	-0.24475**
	(0.09368)	(0.0982)
Meeting two times	-0.02757	-0.04030
	(0.05339)	(0.04540)
Controls		
Student Characteristics	No	Yes
Class Characteristics	Yes	Yes
R-squared	0.0078	0.44
No. Observations	5280	3995

Notes:
Student Characteristics: ACT Composite, ACT Math, Credit Load, Full-time Status, Age, Marital Status, Major, Race: White, Black, Asian, and Hispanic. Classification: Freshman, Sophomore, Junior, and Senior. Class Characteristics: Actual Enrollment, Maximum Enrollment, Honor, and Instructor.

Standard errors are in parentheses; ***, **, and * indicate statistical significance at 1, 5 and 10 percent levels.

The dependent variable is the letter grade in MICRO.

Table 2.4 Ordinary Least Squares Models of Student Grades by Term Length

Variable	Model 1	Model 2
5 weeks	-0.320	-0.176
	(0.272)	(0.312)
3 weeks	-0.235	-0.156
	(0.321)	(0.340)
Controls		
Student Characteristics	No	Yes
Class Characteristics	Yes	Yes
R-squared	0.124	0.523
No. Observations	5523	4143

Notes:

Student Characteristics: ACT Composite, ACT Math, credit load, Full-time Status, Age, Marital Status, Major, Race: White, Black, Asian, and Hispanic. Classification: Freshman, Sophomore, Junior, and Senior.
Class Characteristics: Actual Enrollment, Maximum Enrollment, Full Term, Honor, and Instructor.

Standard errors are in parentheses; ***, **, and * indicate statistical significance at 1, 5 and 10 percent levels.

The dependent variable is the letter grade in MICRO.

Table 2.5 Term Schedule and Length

Session	Number of Weeks	Sections taught during semester
Full Term	14 weeks	103 sections
May Term S1	3 weeks	4 sections
June Term S2	5 weeks	6 sections
July Term S3	5 weeks	5 sections

CHAPTER III: THE EFFECTS OF TIME SPENT ONLINE ON STUDENT ACHIEVEMENT IN HYBRID PRINCIPLE OF MCROECONOMICS COURSE

Introduction

Hybrid courses are becoming increasingly popular as universities try to increase flexible course options for the increasingly busy and technologically focused student. Hybrid courses are defined as “classes in which instruction takes place in a traditional classroom setting augmented by computer-based or online activities which can replace classroom seat time.” The goal of interaction is ultimately to increase course content mastery and understanding. Interaction with the course content is imperative because it allows for successful course completion and acquisition of knowledge (Jung and Choi, 2002). Moore (1989) identified a three-dimensional construct that characterized interaction as either learner to content, learner to instructor, or learner to learner. In hybrid courses, students get the benefit of face-to-face interaction with more flexibility in coursework online. Many students like taking courses online, but do not want to miss out on the traditional face-to-face component that nurtures their sense of community (Rovai and Jordan, 2004).

Research on supplementary instructional methods through the use of technology in conjunction with traditional face to face learning methods is relatively new. Generally speaking, the literature shows that online material used as supplementary resources and learning activities can lead to improved student outcomes in the classroom.

We study the determinants of academic achievement in principles of microeconomics courses meeting 2 days a week for 170 total minutes, but having online homework assignments and exams. We hypothesize that more time spent online on homework and exams is associated with higher grades. Our data contain the actual time students spend on each online assignment as well as the total time online during an entire semester.

Online homework and exams are becoming increasingly prevalent and can benefit both faculty and students alike. The implementation of online homework allows students to practice and apply concepts, as well as to receive feedback, on their own schedule. In turn, this allows for more flexibility for faculty and students as well as more practice for students (Dillard-Eggers, 2011). Another benefit is the use of computer algorithms that give students different questions in order to ensure academic integrity and increase the number of problems on which students work. Online homework also benefits students who prefer using computers and associated technology. Studies by Peng and Michelson (2006) and Smith (2004) confirm this, finding that students who have a positive view of internet-based resources are more motivated to improve their learning experience by using web-based enhancements.

As online homework and exams become increasingly accepted, it is important for educators and administrators to study ways in which they can adapt to the new technology. More efficient grading of student work allows faculty to spend more time developing curriculum. Furthermore, computer grading may lead to fewer mistakes in grading, which again saves time for both students and instructors.

As the number of hybrid courses and online course offerings in universities and colleges continues to escalate, it is imperative to determine what makes such courses successful for students. A recent survey of higher education in the United States by Babson Survey Research Group reported that more than 5.8 million students are currently enrolled in online courses

(Allen, Seaman, Sloan, Babson Survey Research, & Pearson, 2013). It is beneficial to determine the effectiveness of online participation in student achievement. For example, if particular online participation aspects such as discussion boards, forums, and other areas of e-learning are found to affect performance outcomes positively, course delivery can be modified to use the most effective aspects. This can help administrators, instructors, and educators, as well as website and curriculum developers, to offer the best education possible to students.

Furthermore, academic success is still not very well understood. Many studies focusing on the academic achievement of students according to mode of instruction find that online students significantly underperform their peers in traditional classrooms (Coates, Humphreys, Kane, and Vachris, 2004; Farinella, 2007). One possible conclusion from this discrepancy is that further efforts are needed to better understand the factors contributing to success in hybrid and online classes.

We analyze data from the Office of Institutional Effectiveness, Planning, and Research (IEPR) at Middle Tennessee State University (MTSU) and MyEconLab. The sample contains data for 325 students who took microeconomics. We present ordinary least squares estimates (OLS) for the effects of time spent on online assignments on student achievement. We find that time is a significant determinant of exam scores and final grades; more time spent online is associated with higher scores and grades. An additional hour spent on online exams improves a student's grade by 0.42 GPA. Online homework is less productive: if a student spends 5 hours more on online homework, it may improve that student's grade by 0.34 GPA. Section 2 reviews the literature on online learning. Section 3 lays out our empirical methodology, while section 4 describes the data. Results are described in section 5, followed by a conclusion in section 6.

Literature Review

The literature on hybrid courses investigates their impact on student learning, focuses on the effect of teacher-student interaction on student grades, or examines other factors such as computer materials (Killian and Willhite, 2003; Sauers and Walker, 2004; Hofer, 2004; and Lindsay, 2004).

Scida and Saury (2006) study the impact of hybrid courses that met on campus, but had homework assignments and examinations online. Web based homework and practice activities were required for students for two hours. The authors examined student achievement data and student surveys. They found that hybrid courses can be very effective for students and that increased coursework was very helpful compared to traditional methods. Similarly, Smolira (2008) interviewed students in an introductory finance course to determine their perceptions of online coursework. The results indicated that online homework was preferred over traditional homework assignments that were turned in to the instructor.

Bonham, Beichner, and Deardor (2001) compared student performance in classes that used web-assignments for homework to those that used the traditional paper format. The study found no major differences between the classes, except that the web-assign class reported spending more time on the material outside of the classroom.

Dillard-Eggers, et al (2011) evaluated the effect that online homework had on students in a principles of accounting course. The authors surveyed students on their perceptions of the effectiveness of online homework. The authors determined that online homework did in fact increase student performance. Furthermore, students indicated that online homework was an effective study method.

Liberatore (2011) examined online homework and student achievement. The author used customized differentiated online homework to supplement quizzes, exams, and textbook homework. Comparing final grades of students who used traditional homework to those who used online homework, the online environment led to statistically better quiz, exam, and final course grades. Ninety-one percent of students who used online homework received a grade of C or higher for the final course grade, whereas only 72 percent of students in the (traditional) control group attained a C or above. Furthermore, 66 percent of students preferred a combination of textbook and online homework to increase their own learning.

Butler and Zerr (2005) analyzed the use of online homework systems at two public universities. They determined that students were partial to the new system and believed that online assignments were beneficial to their learning. Additionally, students were more engaged by the attempt-feedback-reattempt homework that was available in the online environment.

The use of online learning management systems has also become more popular for examinations. Stowell and Bennett (2010) examined the psychological effects of test anxiety in traditional on-ground courses as opposed to online learning systems for 69 students taking the same course. The authors determined that reduced test anxiety occurred in the online setting compared to on-ground courses. There was a weaker relationship between test anxiety and exam performance in the online environment.

Much research has been done on the differences between on-ground and online course environments, as well as on how these differences impact student achievement. Stern (2004) examined the difference between online and face-to-face course formats. The author found that student success in online courses required them to be familiar with their own learning styles and to have high desire and self-discipline. Additionally, the most important factors in online performance were student time management and organization skills.

One of the biggest issues in online learning is how to effectively improve online participation in coursework (Bento and Schuster, 2003). Morris, Finnegan and Wu (2005) examined student engagement in online courses by analyzing the relationship between student online behavior and student achievement. They monitored 13 sections of three undergraduate general education courses totaling 354 students. Student access computer logs were used to determine participation. There were significant differences in student performance for those who completed the course modules and achieved higher participation levels.

Many articles have addressed the effect of student learning behaviors in nontraditional coursework on student outcomes. Beaudoin (2002) did a case study of inactive students in an online graduate course to determine the reasons for these students' invisibility. The author discovered that students do, in fact, spend a lot of time on learning related tasks and work even if it is not visible. Moreover, these students felt that they were learning and benefiting from the online environment. Another study (Broadbent, 2016) surveyed 310 students in a first year subject, finding that frequency of use was not highly related to student outcomes. Instead, students' belief in their ability to succeed was a stronger indicator of student success.

Shotwell and Apigian (2015) examined differences in student learning in online and traditional Business Statistics classes. A survey showed that students actually received more instructional time in the classroom compared to online, even if they visited the online learning system frequently. Nevertheless, student outcomes were slightly higher among students in the online classes.

Harmon and Lambrinos (2008) uniquely eliminated self-selection bias by studying learners in a course that had both kinds of instructional modes. They also used exam items as a method of observation. The authors determined that online teaching modes did not hinder learning outcomes compared to face-to-face, on-ground instruction in a MBA introductory economics course. Students also had a significantly higher chance of answering an assessment item correctly if it came from a chapter that was taught in the online environment.

Nevertheless, whether extra time students spend studying enhances performance remains unclear (Rich, 2006). Korkofigas and Macri (2013) used a regression modeling strategy to determine if there was a significant relationship between time spent by a student using the course content and assessed performance for a large third year business forecasting class. They used data available through Blackboard, a web-based course content delivery system, to calculate the time each student spent on online assessment activities over the course of the semester. Increased time spent on the online course website was associated with higher assessment performance.

Damianov et al (2009) obtained data on students enrolled in online business courses at a large public university in Texas that included the track record of student activities as well as academic and demographic information. They found a significant relationship between time spent online and grades in the course. Furthermore, the authors determined that more activity was more likely to help a student pass the class. However, there was no significant difference in time spent between students who achieved an A and students who received a B.

Calafiore and Damianov (2011) determined that prior GPA and actual time spent online were associated with higher student outcomes and grades in online courses in economics and finance. The online tracking feature in Blackboard (Campus Edition) was used to retrieve the real time that each student spent on the course for the entire semester. Their analysis included time spent online, prior grade point average (GPA), and demographic characteristics of students. Both higher GPAs and longer time spent online were associated with higher grades. The largest effect of time was on the odds of passing versus failing. Students who did not participate were much more likely to fail than students who were active in the online environment. The authors found that students with a GPA of 3.0 increased their chance of earning an A and reduced their chances of receiving a lower grade. Similarly, a student with a GPA of 2.0 increased his/her chances of earning an A, B, or C and decreased his/her odds of earning a D or a failing grade. The authors estimated that earning a different letter grade could be changed by just spending one more hour per week, thus increasing probabilities of mobility in the final course grade.

Still other literature examines the benefit of online discussion in promoting student-centered learning. Davies and Graff (2005) examined the online interaction of 122 undergraduates and compared their end of year grades. Students' accesses to group and communication areas were combined to measure participation. Among other findings, it was concluded that students who failed in one or more modules interacted less frequently than students who achieved passing grades (Davies and Graff, 2005). This suggests that online discussion improves and increases student performance. Although greater online interaction did not yield higher performance for students who had passing grades, students who failed interacted less frequently.

Several studies have examined the predictors of student outcomes. Thurmond (2003) found that the foremost significant factor in student outcomes was students' perceptions about their interaction with their instructors. The second was perception of technology as contributing to wasted time. Third, students who did not miss the face-to-face interactions were much more satisfied with online learning platforms. Finally, distance from campus helped in predicting satisfaction and likelihood of enrolling in other similar courses. These four variables contributed 72 percent of the variance in predicting satisfaction and 60 percent in likelihood of enrolling in future online courses, showing that students have many different perceptions about online learning related to student achievement.

Gender also may affect online student participation and student achievement. Caspi, Chajut, and Saporta (2008) found that men over-proportionately spoke in the face-to-face classroom, whereas women over-proportionately posted messages in the web-based environment. Thus, women are more likely to participate and overachieve in the online environment. However, Hutson-Stone et al (2014) explored student participation and engagement by gender in a sophomore ethics course at Indiana University and determined few significant differences in online engagement. In the end, they concluded that there was not enough data to definitively determine gender difference in the online classroom.

Yeboah and Smith (2016) found that factors such as language, personality, culture, and efficacy skills facilitated the academic achievement of minority students in the online learning environment. This study concluded that it was imperative to have a multicultural presence in online courses.

Coates, Humphreys, Kane, and Vachris (2004) determined that students in an online principles of economics class had lower student achievement than their peers in on-ground courses. Similarly, Farinella (2007) found that students in an online introduction to finance class achieved significantly lower outcomes than students in traditional sections of the same course. Anstine and Skidmore (2005) analyzed a small sample of traditional and online courses with sample selection adjustment. The authors found that, when controlling for other factors, the online environment could be inferior to the traditional format for MBA students.

A number of these studies stand in contrast to the literature that finds no significant difference in achievement between online and on-ground courses. One conclusion that economic educators can draw from this is that further research must be conducted in order to better understand the factors that lead to success in online and hybrid courses.

Empirical Strategy

Our study attempts to estimate the effects on student grades of online time spent doing homework and exams in five hybrid courses, controlling for student and class characteristics. We hypothesize that more time spent online on homework and exams is associated with higher exam scores and higher grades. The same instructor taught each of the five hybrid courses. The teaching methods and grading procedures remained the same. Thus, there are no variations in grading standards. Each course met two days a week on-campus for 85 minutes each day. There were 17 online homework assignments and four exams. Total time spent online, time spent on homework assignments, and time spent on exams are the main focus variables.

To estimate the effect of time spent online on a student's grade in principles of microeconomics classes, we use an education production function approach in which student performance is a function of student and class characteristics (Cortes, K. E., Bricker, J., and Rohlfs, C., 2010).

Our initial OLS model is:

$$GRADE_i = C + \beta_1 \, TotalTime + \gamma \, 'studentcharacteristics + \delta \, 'classcharacteristics + \varepsilon_i \quad (1)$$

The dependent variable is the letter grade at the end of the term, where $GRADE_i$ is student i's grade on a scale from 0 to 4, with 0 representing a grade of F and 4 representing a grade of A. I also included plus and minus grades. For example, 3.33 represents a grade of B+ and 2.67 represents a grade of B-. $TotalTime$ is either the total time spent online, total homework time spent, or total time spent on exams in separate OLS regressions. The coefficients of these variables are the focus in this model. The finding of a significant positive coefficient would indicate that time spent online is associated with higher grades. Student characteristics include: $GENDER_i$ a dummy variable that equals 1 if the student is a male; credit_i represents the student's credit hours load; ACT_i represents the student's ACT score; AGE $_i$ is the age of the student; $Classification_i$ stands for student's semester hours. For undergraduate students, freshman, sophomore, junior, and senior standing for classifications are determined by earned semester hours. Freshman students have taken less than 32 semester hours; sophomores have taken at least 32 semester hours but less than 64 semester hours; juniors have completed at least 64 semester hours but less than 96 semester hours, and seniors have taken at least 96 semester hours. Class characteristics include: Size $_i$ represents the size of the class in which student i is enrolled.

We also investigated the determinants of the scores on each exam as a function of time spent on the exam, time spent on the homework leading to that exam, and the same student and class characteristics as above. The initial model here is:

$$EXAMSCORE_i = C + \beta_1 \, Examtime + \beta_2 \, Hwtime + \gamma \,'studentcharacteristics + \delta \,'classcharacteristics + \varepsilon_i \quad (2)$$

Where $EXAMSCORE$ is the student's score on the exam out of 100; $Examtime$ is the time spent on the exam online; and $Hwtime$ is the time spent on the online homework for the chapters covered by the exam. We also tested for nonlinear relationships by including the square and the cube of $Examtime$ in some specifications. Interactions of $Examtime$ and $Hwtime$ with ACT scores or GPA's were included to test for further effects of student ability on the productivity of online time. Dummy variables were added for the last three of the four exams to test for "trends" as the semester progressed.

As always in studies of student performance, measuring the effect of variations in ability across students is problematic. We use two measures of student ability and past educational experiences: ACT scores and grade point average or GPA. We do not include both in the same regression, because GPA is likely a function of ACT score. Indeed, the two measure ability in different ways. The ACT score better represents ability and educational experience BEFORE college, whereas GPA better captures a student's history of performance at the college level.

Further, due to missing values, GPA specifications yield over 400 more observations than the ACT score specifications. We report results for both.

Data

We obtained the data for principles of microeconomics courses during the Spring and Fall semesters of 2008-2016. The data come from two sources. The first was the Office of Institutional Effectiveness, Planning, and Research at Middle Tennessee State University for class and student characteristics. These data include information on students' gender, grade, age, race, major, grade point average (GPA), marital status, credit load, and ACT scores.

The second source was MyEconLab for detailed records of the time students' spent on online activities for the entire semester. This included the time spent on each of the 17 homework assignments and on each of the four exams.

In these courses, students met face-to-face with the instructor twice a week. The instructor was a full-time, tenure track faculty member. We merged both databases and eliminated any data that could lead to the identification of an individual student. From the initial sample, we removed students who voluntarily dropped the course and those that had an incomplete final grade. The final sample for the GRADE regressions consists of 325 students who enrolled in and received a grade in one of these five Hybrid courses during the Fall or Spring semesters of the 2008-2016 academic years. This instructor did not teach the microeconomics principles class in every semester. The final sample consisted of 110 female and 215 male students, aged 18 to 43 years.

Most previous research depended on self-reported data that reflected students' perceptions of time spent, rather than measuring time spent in learning activities (Rich, 2006). Technology enabled us to capture the actual time students spent on online activity. The tracking features of web-based learning (e.g., MyEconLab) made it possible to retrieve the real time that students spent online doing things such as homework and exams during a specified period of time.

Table 1 presents descriptive statistics of student and class characteristics. 66% of the students surveyed were male and 43% were female. The mean for student grades was 2.79 with an average ACT score of 22.09. The average credit load was 12.75 credits, and 81.54% of students were enrolled full time. The average age for the students was 23.14. Regarding marital status 64% of the students were single, while 4.62% were married, 1.23% were divorced or separated. In terms of race and ethnicity 59.69% of students were White, while 17.85% were Black, 11.69% were Asian, and 2.15% were Hispanic. The average class size was 77.56.

Majors included 16.62% Business Administration majors; 13.85% Information Systems majors; 13.54% Accounting majors, 12% Finance majors, 8.62% Marketing majors, 4.92% Management majors, and 3.08% were Economics majors. The time spent during online activity showed that the mean total exam time spent was 198 minutes (3.30 hours). The mean total homework assignments time spent was 546 minutes (9.10 hours). The mean total time spent online was 744 minutes (12.41 hours). The class standing of the sample was: 31% of students were Freshmen; 25.54% were Sophomores; 20.31% were Juniors, and 41.32% were Seniors.

Table 10 presents descriptive statistics of the scores on each exam as a function of time spent on the exam and time spent on the homework leading to that exam. The mean exam score was 65.60 with an average exam time of 49.57. The average homework time was 188. There are 1300 observations.

Results

Table 2 presents the results of the ordinary least squares (OLS) regression. The estimated coefficient on total time is positive and statistically significant at the 1 percent level; a minute increase in total time spent during an online activity improved grades by 0.0011 when the other variables were held constant. If a student spent 5 hours more during total online activity time in a class, it improved a student's grades by 0.34 GPA which could change a student's grade from a C+ to a B.

Table 3 presents the results of the ordinary least squares (OLS) regression for the effect of Total Exam Time on students' grades. The estimated coefficient is positive and statistically significant at the 1 percent level; a one minute increase in Total Exam Time improved a student's grade by 0.007 holding the other variables constant. If a student spent an hour more during online exams, it improved a student's grade by 0.42 GPA which could change a student's grades from B+ to A. The mean total exam time spent was 198 minutes (3.30 hours). Students were given 85 minutes for each of the four exams for a total of 340 minutes.

Table 4 presents the results for the ordinary least squares (OLS) regression for the effect of Total Homework Time on students' grades. The estimated coefficient is positive and statistically significant at the 1 percent level: a minute increase in total time spent on homework assignments improved grades by 0.0011 when the other variables were held constant. If a student spent 5 hours more on online homework assignments, it improved a student's grades by 0.34 GPA which could change a student's grade from a B+ to an A. The mean total time spent on homework assignments was 546 minutes (9.10 hours). Students had unlimited time for each of the 17 homework assignments. Thus, time was a significant determinant of the final grade; a longer time spent online was associated with higher grades.

Table 5 presents the results for the ordinary least squares (OLS) regression for both the effect of Total Homework Time and Total Exam Time on students' grades on one regression. The estimated coefficient for Total Homework Time is positive and statistically significant at the 1 percent level: a minute increase in total time spent on homework assignments improved grades by 0.001 when the other variables were held constant. If a student spent 5 hours more during online homework assignments, it improved a student's grades by 0.34 GPA. The estimated coefficient for Total Exam Time is positive and statistically significant at the 1 percent level; a minute increase in Total Exam Time improved a student's grade by 0.005 holding the other variables constant. If a student spent an hour more on online exams, it improved a student's grade by 0.42 GPA.

In order to confirm our analysis and check for robustness, we ran separate OLS regressions using numerical scores on each exam as the dependent variable. This also increased the number of observations by a factor of four. Table 6 presents the results for the ordinary least squares regression for the effect of exam time and homework time on students' exam grades using ACT score to control for ability. Table 7 presents the results for the ordinary least squares regression for the effect of exam time and homework time on students' exam grades using GPA to control for ability. In both the ACT and GPA specifications, exam time is positively and significantly related to exam score, as we expected, but homework time is not significant and has an unexpected negative sign.

Table 6 shows that the estimated coefficient on exam time is positive and statistically significant at the 1 percent level; a one minute increase in time spent during an online exam improved exam score by 0.79. While table 7 shows that the estimated coefficient on exam time is positive and statistically significant at the 1 percent level; a one minute increase in time spent during an online exam improved exam score by 0.83.

Table 8 presents the results for the ordinary least squares regression for the effect of exam time and homework time on students' exam score with ACT control and ACT interactions with exam time. The estimated coefficients on all exam time variables are statistically significant at the 1 percent level, indicating a non-linear relationship between exam time and exam score. The homework time coefficient is not significant, although it is positive. The ACT-exam time interaction coefficient is positive and significant, indicating that higher "ability" increases the productivity of time spent on the exam.

Table 9 presents the results for the ordinary least squares regression for the effect of exam time and homework time on students' exam score with GPA control and GPA interactions with exam time. The estimated coefficients on the exam time variables are statistically significant at the 1 percent level, again indicating a nonlinear relationship. The homework time coefficient is positive and significant at about the 2 percent level, but the effect is very small. The GPA-examtime interaction coefficient is positive and significant at 1 percent, again indicating that higher "ability" makes the time spent on an exam more productive.

The later specifications make specific additions to test specific hypotheses. Adding exam time squared and cubed tests for a nonlinear relationship between exam score and exam time. Since these coefficients are significant, the relationship appears to be nonlinear. Figure 3.1 of the cubic equation for exam score with GPA=4 against exam time has three inflection points: it increases to a peak, decreases to a trough, and then increases again. The peak at 45 minutes and score of 88.75, the trough at 71 minutes and score of 84.28, and then peak at 85 minutes and score of 89.75. Figure 3.2 of the cubic equation for exam score with GPA=1 against exam time has inflection two points: it increases to a peak, and then decreases to a trough. The peak at 39 minutes and score of 75.02, and then trough at 77 minutes and score of 59.76.

The interactions of exam time with ACT and GPA test for whether higher ability increases the productivity of time spent on the exam. Since the interactions are positive and significant, higher ability seems to raise the productivity of time spent on the exam. However, in Table 8, the addition of the ACT interaction causes the ACT coefficient to become insignificant, suggesting no independent effect of ability aside from its raising the productivity of time spent on the exam. The results for GPA in Table 9 are not consistent with this conclusion, however. The GPA-examtime coefficient is positive and significant, but so is the GPA coefficient. This suggests that ability measured by GPA has an independent effect on exam scores over and above raising the productivity of time spent on the exam.

Further, in the cubic specifications in tables 8 and 9, Homework Time becomes positive, but significant only in Table 9, although the size of the effect in both cases is very small. We also tried interactions of ACT and GPA with homework time, but these were all insignificant. Apparently, our ability measures affect exam scores directly without affecting the productivity of time spent on homework. The small effect of homework time may reflect the students' ability to spend unlimited time on the homework prior to the due date. Most students scored over 90 on each homework assignment. Hence, the marginal effect of more homework time may be small.

Conclusion

Higher education is becoming progressively more expensive for students. Tuition and enrollment alike are becoming of increasing concern for administrators, instructors, and students. It is thus imperative to determine the most effective ways to provide a high-quality education at a reasonable cost. However, the recent decrease in government spending and funding has led many public universities to offer fewer course sections, which has the effect of increasing class size on the class sections that are available, and add more online classes.

Previous literature shows that online material used as learning activities led to increased student outcomes in the classroom. This study shows that hybrid courses, as flexible course options for the increasingly busy faculties and students, can have high learning outcomes and high achievement. Online homework assignments and exams can benefit both faculty and students alike. We hypothesized that students would have better learning outcomes and higher achievement when they spend more time online on homework and exams. Despite the fact that students did not utilize the full allotted exam time, our results show that time is a significant determinant of the final grade; a longer time spent in online activities is associated with higher grades in microeconomics.

Online homework and exams will also save faculty resources by reducing time spent manually grading the coursework. Faculty members who use online homework can save valuable time and resources. Many educators feel homework is necessary, yet they have large class sizes to accommodate. However, online programs have the capability to grade homework and exams automatically through computer algorithms, thus saving time while helping students to learn. One motivation that administrators might consider is that Hybrid courses can be an efficient way to deliver education, allowing faculty to teach more students by taking advantage of new technology. Large increases in efficiency can help reduce alternative costs such as time spent, as well as actual costs associated with teaching faculty and support staff (Allen and Seaman, 2013).

Our study focused on the function of time spent in online activities on academic performance. One factor that is unaccounted for is student effort. We believed that the total amount of time spent on a course was a good measure of student effort. The frequency of course website usage by students may be an alternative variable which could count the number of times a student has logged into the course for the entire semester. This variable could, however, be significantly correlated with all other variables. In contrast, Calafiore and Damianov (2011) found that time spent on the course is a stronger determinant of student performance than the number of times a student logs into the course website. Alternative measures of effort in online activity can be the number of messages posted on discussion boards. An analysis of the number of times a student logged into the course measures and the number of messages posted on discussion boards might demonstrate the ways students learn and which activities contribute to students’ performance.

REFERENCES

Allen, I. E., Seaman, J., Sloan, C., Babson Survey Research, G., & Pearson, F. (2013). *Changing course: Ten years of tracking online education in the united states* (978-0-9840-2883-2). Retrieved from https://ezproxy.mtsu.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=ED541571&site=eds-live&scope=site

Angus, S. D., & Watson, J. (2009). Does regular online testing enhance student learning in the numerical sciences? Robust evidence from a large data set. *British Journal of Educational Technology, 40*(2), 255-272.

Anstine, J., & Skidmore, M. (2005). A small sample study of traditional and online courses with sample selection adjustment. *The Journal of Economic Education, 36*(2), 107-127.

Beaudoin, M. F. (2002). Learning or lurking?: Tracking the "invisible" online student. *The Internet and Higher Education, 5*(2), 147-155.

Bento, R., & Schuster, C. (2003). Participation: The online challenge. *Web-Based Education: Learning from Experience*, Vol. 4, 156-164.

Bonham, S., Beichner, R., & Deardorff, D. (2001). Online homework: Does it make a difference? *The Physics Teacher, 39*(5), 293-296.

Broadbent, J. (2016). Academic success is about self-efficacy rather than frequency of use of the learning management system. *Australasian Journal of Educational Technology, 32*(4).

Brothen, T., & Peterson, G. (2012). Online exam cheating: A natural experiment. *International Journal of Instructional Technology and Distance Learning, 9*(2), 15-20.

Butler, M. B., & Zerr, R. J. (2005). The use of online homework systems to enhance out-of-class student engagement. *International Journal for Technology in Mathematics Education, 12*(2).

Calafiore, P., & Damianov, D. S. (2011). The effect of time spent online on student achievement in online economics and finance courses. *The Journal of Economic Education, 42*(3), 209-223.

Caspi, A., Chajut, E., & Saporta, K. (2008). Participation in class and in online discussions: Gender differences. *Computers & Education, 50*(3), 718-724.

Coates, D., Humphreys, B. R., Kane, J., & Vachris, M. A. (2004). “No significant distance” between face-to-face and online instruction: Evidence from principles of economics. *Economics of Education Review, 23*(5), 533-546.

Cortes, K. E., Bricker, J., & Rohlfs, C. (2012). The role of specific subjects in education production functions: Evidence from morning classes in Chicago public high schools. *The BE Journal of Economic Analysis & Policy, 12*(1).

Damianov, D. S., Kupczynski, L., Calafiore, P., Damianova, E. P., Soydemir, G., & Gonzalez, E. (2009). Time spent online and student performance in online business courses: A multinomial logit analysis. *Journal of Economics and Finance Education, 8*(2), 11-22.

Davies, J., & Graff, M. (2005). Performance in e-learning: online participation and student grades. *British Journal of Educational Technology*, *36*(4), 657-663.

Desouza, E., & Fleming, M. (2003). A comparison of in-class and online quizzes on student exam performance. *Journal of Computing in Higher Education*, *14*(2), 121-134.

Dillard-Eggers, J., Wooten, T., Childs, B., & Coker, J. (2011). Evidence on the effectiveness of on-line homework. *College Teaching Methods & Styles Journal (CTMS), 4*(5), 9-16.

Farinella, J. (2007). Professor and student performance in online versus traditional introductory finance courses. *Journal of Economics and Finance Education*, *6*(1), 40-47.

Harmon, O., & Lambrinos, J. (2008). Student performance in traditional vs. online format: Evidence from introductory economics classes. *Southern Economic Journal*, *3*, 1-15.

Hofer, M. (2004). Online digital archives technology that supports rich, student-centered learning experiences. *Learning & Leading with Technology, 32*(2).

Hutson-Stone, A. D., Little-Wiles, J. M., Fernandez, E., & Fox, P. (2014). *Student Engagement Online–Does Gender Make a Difference? A Pilot Study in One Engineering and Technology Course.* Paper presented at the 2014 ASEE Annual Conference & Exposition (pp. 24-1112).

Jung, I., Choi, S., Lim, C., & Leem, J. (2002). Effects of different types of interaction on learning achievement, satisfaction and participation in web-based instruction. *Innovations in Education and Teaching International*, *39*(2), 153-162.

Killian, J., & Willhite, G. L. (2003). Electronic discourse in preservice teacher preparation. *Journal of Technology and Teacher Education, 11*(3), 377-395.

Korkofingas, C., & Macri, J. (2013). Does time spent online have an influence on student performance? Evidence for a large business studies class. *Journal of University Teaching & Learning Practice, 10*(2), 2.

Larsen, K. G., Mikucionis, M., & Nielsen, B. (2004). Online testing of real-time systems using uppaal. *Lecture Notes in Computer Science, 4,* 79-94.

Liberatore, M. W. (2011). Improved student achievement using personalized online homework. *Chemical Engineering Education, 45*(3), 184-190.

Lindsay, E. B. (2004). The best of both worlds: teaching a hybrid course. *Academic Exchange Quarterly, 4*, 16.

Michelson, S., & Smith, S. (2004). Web usage in financial education. *Advances in Financial Education, 2*, 22-33.

Moore, M. G. (1989). Editorial: Three types of interaction. *American Journal of Distance Education, 1*,1.

Morris, L. V., Finnegan, C., & Wu, S.-S. (2005). Tracking student behavior, persistence, and achievement in online courses. *The Internet and Higher Education, 8*(3), 221-231.

Peng, Z. (2006). Applying internet-based technologies to teaching corporate finance and investments. *Journal of Educators Online, 3*(1).

Rich, S. P. (2006). Student performance: does effort matter? *Journal of Applied Finance, 16*(2), 120.

Rovai, A. P., & Jordan, H. (2004). Blended learning and sense of community: A comparative analysis with traditional and fully online graduate courses. *The International Review of Research in Open and Distributed Learning, 5*(2).

Sarrayrih, M. A., & Ilyas, M. (2013). Challenges of online exam, performances and problems for online university exam. *IJCSI International Journal of Computer Science Issues, 10*(1), 1694-0784.

Sauers, D., & Walker, R. C. (2004). A comparison of traditional and technology-assisted instructional methods in the business communication classroom. *Business Communication Quarterly, 67*(4), 430-442.

Scida, E. E., & Saury, R. E. (2006). Hybrid courses and their impact on student and classroom performance: A case study at the University of Virginia. *Calico Journal*, *23*(3), 517-531.

Shotwell, M., & Apigian, C. H. (2015). Student performance and success factors in learning business statistics in online vs. on-ground classes using a web-based assessment platform. *Journal of Statistics Education, 23*(1), 1-19.

Smolira, J. C. (2008). Student perceptions of online homework in introductory finance courses. *Journal of Education for Business, 84*(2), 90-95.

Stern, B. S. (2004). A comparison of online and face-to-face instruction in an undergraduate foundations of American education course. *Contemporary Issues in Technology and Teacher Education, 4*(2), 196-213.

Stowell, J. R., & Bennett, D. (2010). Effects of online testing on student exam performance and test anxiety. *Journal of Educational Computing Research, 42*(2), 161-171.

Thurmond, V. A. (2003). *Examination of interaction variables as predictors of students' satisfaction and willingness to enroll in future Web-based courses while controlling for student characteristics.*Parkland, Florida: Universal-Publishers.

Vacha, E. F., & McBride, M. J. (1993). Cramming: A barrier to student success, a way to beat the system or an effective learning strategy? *College Student Journal, 27*(1), 2-11.

Yeboah, A. K., & Smith, P. (2016). Relationships between minority students online learning experiences and academic performance. *Online Learning, 20*(4).

APPENDICES

APPENDIX A: TABLES

Table 3.1 Descriptive Statistics: Student Characteristics and Class Characteristics

Variable	Observations	Mean	Std. Dev.	Min	Max
Student Characteristics					
Grades	317	2.79	1.00	0	4
ACT Composite	210	22.09	3.73	14	34
ACT Math	209	20.78	3.81	14	31
Credit load	325	12.75	3.95	3	21
Full time	325	81.54%	38.86%	0	1
GPA Cumulative	324	2.90	0.59	1.02	4
Age	325	23.14	3.55	18	43
Race					
White	325	59.69%	49.13%	0	1
Black	325	17.85%	38.35%	0	1
Asian	325	11.69%	32.18%	0	1
Hispanic	325	2.15%	14.54%	0	1
Marital Status					
Single	325	64.00%	48.07%	0	1
Married	325	4.62%	21.01%	0	1
Divorced or Separated	325	1.23%	11.04%	0	1
Male	325	66%	47.39%	0	1
Female	325	43%	47.39%	0	1
Class Characteristics					
Class size	325	77.56	24.14	43	98
Major					
Business Administration	325	16.62%	37.28%	0	1
Information Systems	325	13.85%	34.59%	0	1
Accounting	325	13.54%	34.27%	0	1
Finance	325	12.00%	32.55%	0	1
Marketing	325	8.62%	28.10%	0	1
Management	325	4.92%	21.67%	0	1
Economics	325	3.08%	17.30%	0	1
Time in minutes					
Total Exams time	325	198.30	68.88	0	338
Total Homework time	325	546.42	285.26	0	1394
Total Time	325	744.72	310.65	0	1713
Classification					
Freshman	325	8.31%	27.64%	0	1
Sophomore	325	25.54%	43.67%	0	1
Junior	325	20.31%	40.29%	0	1
Senior	325	41.23%	49.30%	0	1

Table 3.2 Ordinary Least Squares Models for Total Time Spent

Variable	Coefficient	Standard Error	t	P>|t|
Total Time	0.0011	0.0002	5.41	0.000
ACT Composite	0.066	0.029	2.29	0.023
ACT Math	0.021	0.028	0.75	0.456
Credit load	0.006	0.033	0.18	0.857
Full time	0.162	0.318	0.51	0.610
Age	0.037	0.033	1.12	0.266
Race				
White	0.377	0.269	1.40	0.163
Black	0.179	0.290	0.62	0.538
Asian	0.276	0.370	0.75	0.457
Hispanic	0.339	0.581	0.58	0.560
Marital Status				
Single	0.229	0.176	1.30	0.195
Married	0.823	0.496	1.66	0.099
Divorced or Separated	-0.437	0.908	-0.48	0.631
Male	0.008	0.004	1.95	0.053
Class Characteristics				
Class size	0.091	0.137	0.66	0.509
Major				
Accounting	0.040	0.203	0.19	0.846
Business Administration	-0.064	0.187	-0.34	0.734
Finance	0.270	0.254	1.06	0.289
Economics	-0.012	0.408	-0.03	0.976
information systems	0.423	0.226	1.87	0.063
Marketing	0.502	0.245	2.05	0.042
Management	-0.113	0.284	-0.40	0.691
Classification				
Freshman	-0.193	0.404	-0.48	0.634
Sophomore	-0.485	0.363	-1.33	0.184
Junior	-0.381	0.371	-1.03	0.305
Senior	0.090	0.301	0.30	0.764
Cons.	-2.309	1.166	-1.98	0.049
F-statistic:	3.24	P-value:	0.000	
R-squared	0.32			
No. Observations	205			

Table 3.3 Ordinary Least Squares Models for Total Exam Time Spent

Variable	Coefficient	Standard Error	t	P>|t|
Total ExamTime	0.007	0.001	5.59	0.000
ACT Composite	0.089	1.761	3.03	0.003
ACT Math	0.013	0.028	0.48	0.629
Credit load	0.006	0.033	0.17	0.867
Full time	0.320	0.316	1.01	0.313
Age	0.050	0.033	1.52	0.130
Race				
White	0.310	0.267	1.16	0.246
Black	0.109	0.289	0.38	0.706
Asian	0.308	0.369	0.83	0.406
Hispanic	0.382	0.579	0.66	0.510
Marital Status				
Single	0.181	0.176	1.03	0.303
Married	0.972	0.492	1.98	0.050
Divorced or Separated	-0.393	0.903	-0.44	0.664
Male	0.014	0.004	3.51	0.001
Class Characteristics				
Class size	0.033	0.135	0.24	0.810
Major				
Accounting	-0.038	0.203	-0.19	0.853
Business Administration	0.015	0.187	0.08	0.936
Finance	0.399	0.253	1.58	0.117
Economics	0.167	0.406	0.41	0.682
information systems	0.421	0.225	1.87	0.063
Marketing	0.429	0.244	1.76	0.080
Management	-0.153	0.283	-0.54	0.589
Classification				
Freshman	0.045	0.404	0.11	0.912
Sophomore	-0.401	0.363	-1.11	0.270
Junior	-0.212	0.371	-0.57	0.569
Senior	0.148	0.301	0.49	0.624
Cons.	-4.057	1.260	-3.22	0.002
F-statistic:	3.24	P-value:	0.000	
R-squared	0.32			
No. Observations	205			

Table 3.4 Ordinary Least Squares Models for Total Homework Time Spent

Variable	Coefficient	Standard Error	t	P>|t|
Total Homework Time	0.0011	0.0002	4.69	0.000
ACT Composite	0.061	0.029	2.07	0.040
ACT Math	0.021	0.028	0.75	0.454
Credit load	0.006	0.034	0.18	0.861
Full time	0.153	0.323	0.47	0.636
Age	0.036	0.034	1.08	0.283
Race				
White	0.352	0.274	1.28	0.201
Black	0.177	0.296	0.60	0.551
Asian	0.230	0.377	0.61	0.542
Hispanic	0.341	0.592	0.58	0.566
Marital Status				
Single	0.230	0.180	1.28	0.201
Married	0.845	0.505	1.67	0.096
Divorced or Separated	-0.339	0.924	-0.37	0.714
Male	0.006	0.004	1.56	0.120
Class Characteristics				
Class size	0.074	0.140	0.53	0.596
Major				
Accounting	0.064	0.207	0.31	0.757
Business Administration	-0.077	0.191	-0.40	0.688
Finance	0.258	0.259	1.00	0.320
Economics	-0.025	0.415	-0.06	0.951
information systems	0.429	0.230	1.86	0.064
Marketing	0.513	0.249	2.06	0.041
Management	-0.123	0.289	-0.43	0.671
Classification				
Freshman	-0.226	0.412	-0.55	0.584
Sophomore	-0.519	0.370	-1.40	0.162
Junior	-0.415	0.377	-1.10	0.273
Senior	0.053	0.306	0.17	0.862
Cons.	-1.747	1.172	-1.49	0.138
F-statistic:	2.89	P-value:	0.000	
R-squared	0.29			
No. Observations	205			

Table 3.5 Ordinary Least Squares Models for Total Homework Time Spent and Total Exam Time Spent

Variable	Coefficient	Standard Error	t	P>|t|
Total Homework Time	0.0010	0.000	3.16	0.002
Total Exam Time	0.0052	0.001	4.31	0.000
ACT Composite	0.085	0.029	2.96	0.003
ACT Math	0.017	0.027	0.63	0.533
Credit load	0.0058	0.032	0.18	0.856
Full time	0.243	0.309	0.79	0.433
Age	0.043	0.032	1.35	0.178
Race				
White	0.390	0.262	1.49	0.138
Black	0.153	0.282	0.54	0.588
Asian	0.364	0.361	1.01	0.314
Hispanic	0.355	0.565	0.63	0.530
Marital Status				
Single	0.207	0.171	1.21	0.228
Married	0.851	0.481	1.77	0.079
Divorced or Separated	-0.578	0.883	-0.65	0.514
Male	0.013	0.004	3.14	0.002
Class Characteristics				
Class size	0.094	0.134	0.70	0.484
Major				
Accounting	-0.032	0.198	-0.16	0.871
Business Administration	-0.010	0.182	-0.05	0.958
Finance	0.344	0.248	1.39	0.167
Economics	0.085	0.397	0.21	0.831
information systems	0.411	0.220	1.87	0.063
Marketing	0.453	0.238	1.90	0.058
Management	-0.114	0.276	-0.41	0.681
Classification				
Freshman	-0.039	0.395	-0.10	0.922
Sophomore	-0.395	0.354	-1.12	0.266
Junior	-0.255	0.362	-0.70	0.482
Senior	0.175	0.294	0.60	0.552
Cons.	-3.953	1.230	-3.21	0.002
F-statistic:	3.75	P-value:	0.000	
R-squared	0.363			
No. Observations	205			

The dependent variable is the letter grade in microeconomics.

Table 3.6 Ordinary Least Squares Models for Homework Time Spent and Exam Time Spent (with ACT Control)

Variable	Coefficient	Standard Error	t	P>|t|
Exam Time	0.7986	0.027	30.07	0.000
Homework Time	-0.0022	0.002	-1.32	0.187
ACT Composite	1.712	0.331	5.17	0.000
ACT Math	-0.162	0.314	-0.52	0.606
Credit load	0.101	0.381	0.27	0.791
Full time	5.089	3.625	1.40	0.161
Age	0.934	0.377	2.48	0.013
Race				
White	4.300	3.065	1.4	0.161
Black	0.358	3.320	0.11	0.914
Asian	7.103	4.229	1.68	0.093
Hispanic	2.844	6.683	0.43	0.671
Marital Status				
Single	0.558	2.027	0.28	0.783
Married	4.001	5.118	0.78	0.435
Divorced or Separated	-18.329	10.412	-1.76	0.079
Male	0.048	0.044	1.08	0.280
Class Characteristics				
Class size	1.517	1.540	0.98	0.325
Major				
Accounting	-4.396	2.329	-1.89	0.059
Business Administration	2.576	2.120	1.22	0.225
Finance	6.040	2.914	2.07	0.039
Economics	6.088	4.676	1.30	0.193
information systems	2.462	2.554	0.96	0.335
Marketing	3.500	2.806	1.25	0.213
Management	0.169	3.154	0.05	0.957
Classification				
Freshman	-0.398	4.599	-0.09	0.931
Sophomore	-2.426	4.132	-0.59	0.557
Junior	-2.212	4.240	-0.52	0.602
Senior	4.261	3.448	1.24	0.217
Cons.	-46.381	13.366	-3.47	0.001
F-statistic:	39	P-value:	0.000	
R-squared	0.57			
No. Observations	836			

Table 3.7 Ordinary Least Squares Models for Homework Time Spent and Exam Time Spent (with GPA Control)

Variable	Coefficient	Standard Error	t	P>|t|
Exam Time	0.83679	0.023	36.83	0.000
Homework Time	-0.00098	0.001	-0.78	0.437
GPA	7.438	1.141	6.52	0.000
Credit load	-0.207	0.304	-0.68	0.497
Full time	4.954	3.054	1.62	0.105
Age	-0.089	0.207	-0.43	0.667
Race				
White	0.104	2.337	0.04	0.964
Black	-5.865	2.774	-2.11	0.035
Asian	0.328	2.795	0.12	0.907
Hispanic	-4.193	4.778	-0.88	0.380
Marital Status				
Single	-4.754	1.573	-3.02	0.003
Married	4.792	3.257	1.47	0.142
Divorced or Separated	-7.648	5.941	-1.29	0.198
Male	0.082	0.036	2.28	0.023
Class Characteristics				
Class size	3.238	1.417	2.28	0.023
Major				
Accounting	-1.576	2.062	-0.76	0.445
Business Administration	0.997	1.947	0.51	0.609
Finance	7.164	2.216	3.23	0.001
Economics	6.877	3.677	1.87	0.062
information systems	-0.490	2.077	-0.24	0.814
Marketing	-1.061	2.382	-0.45	0.656
Management	-0.727	3.031	-0.24	0.811
Classification				
Freshman	-7.164	4.045	-1.77	0.077
Sophomore	-3.199	3.602	-0.89	0.375
Junior	-1.494	3.637	-0.41	0.681
Senior	1.408	3.200	0.44	0.660
Cons.	-0.722	8.592	-0.08	0.933
F-statistic:	62	P-value:	0.000	
R-squared	0.56			
No. Observations	1296			

The dependent variable is exam grade in microeconomics

Table 3.8 Ordinary Least Squares Models for Homework Time Spent and Exam Time Spent (with ACT Control) and ACT Interactions with Exam Time

Variable	Coefficient	Standard Error	t	P>|t|
Exam Time	4.012	0.148	27.05	0.000
Exam Time Squared	-0.077	0.004	-19.88	0.000
Exam Time Cubic	0.00043	0.000	14.36	0.000
Homework Time	0.00070	0.001	0.73	0.466
Exam_ ACT	0.014	0.004	3.67	0.000
Exam2	0.121	0.017	6.99	0.000
Exam3	0.092	0.014	6.45	0.000
Exam4	0.101	0.014	7.34	0.000
ACT Composite	-0.309	0.264	-1.17	0.242
ACT Math	0.300	0.176	1.70	0.090
Credit load	-0.056	0.214	-0.26	0.792
Full time	2.005	2.041	0.98	0.326
Age	0.570	0.213	2.67	0.008
Race				
White	2.048	1.716	1.19	0.233
Black	0.697	1.867	0.37	0.709
Asian	1.642	2.368	0.69	0.488
Hispanic	1.010	3.875	0.26	0.794
Marital Status				
Single	-0.395	1.138	-0.35	0.729
Married	-0.641	2.929	-0.22	0.827
Divorced or Separated	-0.344	5.967	-0.06	0.954
Male	0.189	0.025	7.48	0.000
Class Characteristics				
Class size	-0.040	0.864	-0.05	0.963
Major				
Accounting	0.0013	1.319	0.00	0.999
Business Administration	1.615	1.199	1.35	0.178
Finance	-1.077	1.656	-0.65	0.516
Economics	5.080	2.667	1.90	0.057
information systems	3.462	1.448	2.39	0.017
Marketing	1.092	1.581	0.69	0.490
Management	-0.288	1.777	-0.16	0.871
Classification				
Freshman	-0.578	2.583	-0.22	0.823
Sophomore	-0.265	2.344	-0.11	0.910
Junior	-2.423	2.405	-1.01	0.314
Senior	1.249	1.954	0.64	0.523
Cons.	-47.602	8.378	-5.68	0.000
F-statistic:	158	P-value:	0.000	
R-squared	0.86			
No. Observations	836			

Table 3.9 Ordinary Least Squares Models for Homework Time Spent and Exam Time Spent (with GPA Control) and GPA Interactions with Exam Time

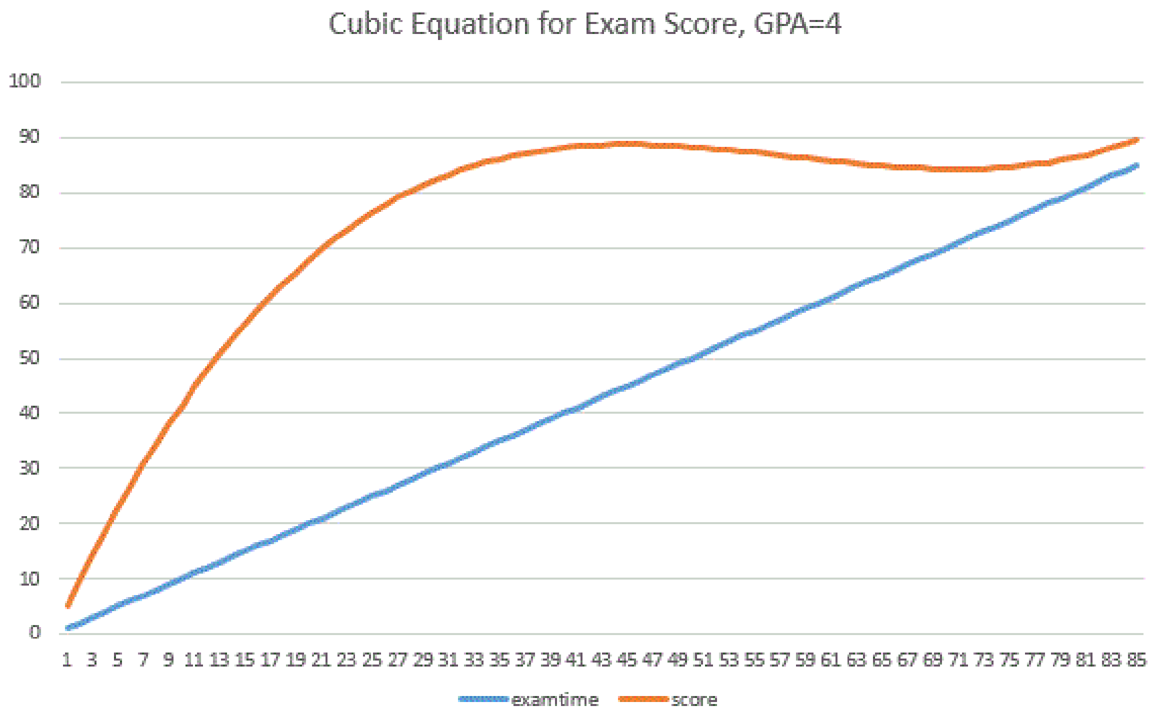
Variable	Coefficient	Standard Error	t	P>|t|
Exam Time	4.55523	0.116	39.32	0.000
Exam Time Squared	-0.09105	0.003	-29.78	0.000
Exam Time Cubic	0.00052	0.000	22.01	0.000
Homework Time	0.00151	0.001	2.34	0.019
Exam_GPA	0.110	0.019	5.92	0.000
Exam2	1.117	1.079	1.03	0.301
Exam3	0.060	0.012	5.01	0.000
Exam4	0.053	0.010	5.25	0.000
GPA	0.073	0.011	6.49	0.000
Credit load	0.010	0.156	0.07	0.947
Full time	0.782	1.566	0.50	0.618
Age	0.182	0.106	1.72	0.086
Race				
White	2.426	1.196	2.03	0.043
Black	0.881	1.417	0.62	0.534
Asian	2.020	1.426	1.42	0.157
Hispanic	0.507	2.455	0.21	0.836
Marital Status				
Single	-3.114	0.821	-3.79	0.000
Married	0.475	1.676	0.28	0.777
Divorced or Separated	-5.757	3.036	-1.90	0.058
Male	0.179	0.018	9.73	0.000
Class Characteristics				
Class size	0.493	0.725	0.68	0.496
Major				
Accounting	-0.698	1.051	-0.66	0.506
Business Administration	0.860	0.992	0.87	0.386
Finance	1.509	1.145	1.32	0.188
Economics	5.564	1.895	2.94	0.003
information systems	2.009	1.063	1.89	0.059
Marketing	0.649	1.222	0.53	0.595
Management	0.846	1.550	0.55	0.585
Classification				
Freshman	-2.068	2.090	-0.99	0.323
Sophomore	-2.565	1.865	-1.38	0.169
Junior	-2.823	1.866	-1.51	0.131
Senior	-1.314	1.635	-0.80	0.421
Cons.	-33.400	5.054	-6.61	0.000
F-statistic:	311	P-value:	0.000	
R-squared	0.88			
No. Observations	1296			

Table 3.10 Descriptive Statistics: of the Scores on Each Exam as a Function of Time Spent on the exam, Time Spent on the Homework Leading to that Exam

Variable	Observations	Mean	Std. Dev.	Min	Max
Exam Scores	1300	65.60	32.20	0	100
Exam Time	1300	49.57	28.29	0	89
Homework Time	1300	188.68	478.89	0	10489
ACT Composite	840	22.09	3.72	14	34
ACT Math	836	20.78	3.80	14	31
Credit load	1300	12.75	3.95	1	21
Full time	1300	82%	39%	0	1
GPA Cumulative	1296	2.90	0.59	1	4
Age	1300	23.14	3.54	18	43
Race					
White	1300	59.69%	49.07%	0	1
Black	1300	17.85%	38.30%	0	1
Asian	1300	11.69%	32.15%	0	1
Hispanic	1300	2.15%	14.52%	0	1
Marital Status					
Single	1300	64%	48%	0	1
Married	1300	4.62%	20.99%	0	1
Divorced or Separated	1300	1.23%	11.03%	0	1
Class size	1300	77.56	24.12	43	98
Male	1300	66.15%	47.34%	0	1
Major					
Accounting	1300	13.54%	34.23%	0	1
Business Administration	1300	16.62%	37.24%	0	1
Finance	1300	12.00%	32.51%	0	1
Economics	1300	3.08%	17.28%	0	1
Information Systems	1300	13.85%	34.55%	0	1
Marketing	1300	8.62%	28.07%	0	1
Management	1300	4.92%	21.64%	0	1
Classification					
Freshman	1300	8.31%	27.61%	0	1
Sophomore	1300	25.54%	43.62%	0	1
Junior	1300	20.31%	40.24%	0	1
Senior	1300	41.23%	49.24%	0	1

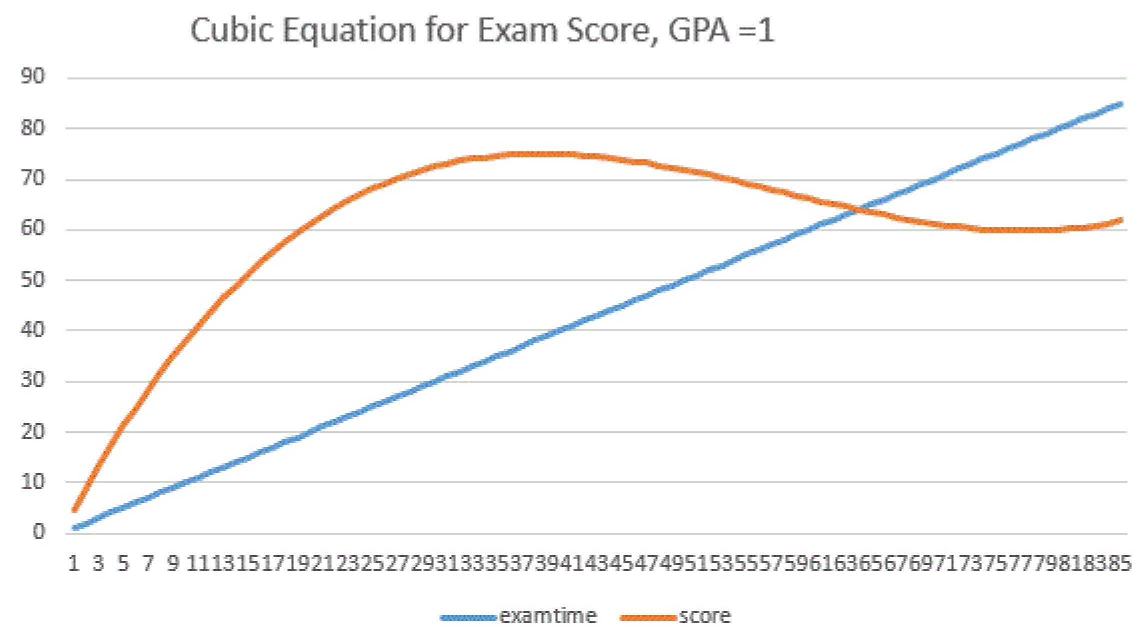
Notes: Time in minutes

APPENDIX B: FIGURES



Peak at 45 minutes and score of 88.75
Trough at 71 minutes and score of 84.28
Peak at 85 minutes and score of 89.75

Figure 3.1 The Nonlinear Effect of Cubic Equation for Exam Score with GPA=4 Against Exam Time



Peak at 39 minutes and score of 75.02
Trough at 77 minutes and score of 59.76

Figure 3.2 The Nonlinear Effect of Cubic Equation for Exam Score with GPA=1 Against Exam Time