Gap between Actual and Expected Time Allocation to Academic Activities and its Impact on Undergraduate Academic Performance

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Abstract

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This study uses survey data and administrative records collected over a three-year period to examine the gap between the amount of time students invested and the amount they were expected to invest in academic activities. The sample includes 2,232 first-year and final-year undergraduate students at an elite research university in Kazakhstan. The study measured time allocation gap in terms of the degree to which the total amount of time invested in academic activities fell short of the expected amount (class attendance and out-of-class study time combined), given the student's credit load. The study found that, on average, undergraduate students (first and fourth year) allocated 35% less time to academic activities than expected under ECTS standards or 28% less time than expected under Carnegie standards. Using a quasi-experimental research design (propensity score matching), the study found that time allocation gap had a negative impact on undergraduate academic performance.

Presentation

Gap between Actual and Expected Time Allocation to Academic Activities and its Impact on Undergraduate Academic Performance

Traditionally, academic programs and courses have been structured in such a way that students devote a certain amount of time to classroom instruction and additional time to out-of-class study. This structure still remains dominant and is perceived as being conducive to learning. Time allocation has been described as a “key indicator of student engagement” (Baik, Naylor, & Arkoudis, 2015, p. 13) in academic activities and an important input in knowledge acquisition and skills development (Babcock & Marks, 2010, 2011). It is a measure of students’ effort which, as Stinebrickner and Stinebrickner (2008) suggest, is “the most fundamental input in the education production function” (p. 1).

Academic credit systems have set standards on the amount of time students taking a certain number of credits should allocate to academic activities. In the Carnegie system, one credit generally corresponds to three hours of academic activities (in and out of class) per week. In the European Credit Transfer System (ECTS) framework, each credit corresponds to 25-30 hours of student work (in and out of class) over the duration of the course (European Union, 2015). The credit hour has been regarded as “the vehicle that allows student learning to be recorded and transferred across many types of institutions” (Shedd, 2003, p. 11). It has been recognized, however, that such time metrics—although adequate for measuring efficiency and productivity (Shedd, 2003)—do not actually measure how much students are learning (Harris, 2002; Shedd, 2003).

The present study examines students’ allocation of time to academic activities within the context an elite research university that blends US and European higher education standards in the Republic of Kazakhstan. The study examines time allocation in terms of the gap between the amount of time students allocated and the amount they were expected to allocate to academic activities based on ECTS and Carnegie credit systems.

Literature Review on Time Allocation and Academic Performance

Amount of Time Allocated to Academic Activities

Researchers have estimated the amount of time undergraduate students allocate to academic activities. Table 1 provides time allocation estimates based on studies conducted in various contexts. These estimates suggest that US students spend around 15 hours for class attendance and 12 to 15 hours for out-of-class study time per week. The total amount of time for US students, 27 to 28 hours per week, was similar to that observed in the UK. Meng and Heijke’s (2005) study of nine European countries found that student allocated around 32 hours per week to academic activities in and out of class, a level of investment similar to the one observed in Australia (Baik et al., 2015; James, Krause, & Jennings, 2010). Although there are variations in country (and even institutional contexts), the overwhelming consensus is that students are no longer investing as much time as they should (or used to) in academic activities. In Australia, James and his colleagues (2010) concluded that “[on] average, students spend less than one hour of study outside of class for every course contact hour” (p. 33). In the USA, McCormick (2011) observed that the level of students’ time investment falls short of “a well-established rule of thumb […] that students should devote two hours of study time for every hour of class time” (p. 39).

Table 1. Student Time Allocation in Different Contexts

Context	Study	Institutions	Data Source(s)	Sample	Lecture Hours Per Week	Study Hours Per Week	Total Hours Per Week
USA							
	Brint & Cantwell (2010)	8 Campuses of University of California system	2006 Undergraduate Experience Survey	6,300 students	15.7	12.2	27.9
	McCormick (2011)	950 four-year institutions	2010 National Survey of Student Engagement (NSSE)	420,000 full-time first-year students & seniors	NA	14.7	NA
	Arum & Roksa (2011)	24 universities	Longitudinal surveys	2,322 undergraduate students	15	12.2	27.2
	Babcock & Marks (2011)	Representative sample of four-year US institutions	Large scale surveys; NLSY79, Talent 1961, 1988 and 2004 HERI, and 2003 NSSE	53,000 full-time undergraduate students	NA	14.4	27
	Ribera, Rocconi, & McCormick (2013)	543 four-year institutions	2011 NSSE	137,000 full-time seniors in 5 professional fields	NA	15.5	NA
Europe							
Multiple countries	Meng & Heijke (2005)		1998 European postal survey	18,532 graduates	17.6	14.8	32.4
Germany	Grave (2010, 2011)	17 universities and technical colleges	1986-2006 Student survey	11,297 Students	18.9	17.3	36.2
UK	Neves & Hillman (2016)	More than 100 institutions	2016 Student Academic Experience Survey	15,221 students	13.5	14.3	27.8
Australia							
	James, Krause, & Jennings (2010)	9 universities	2009 First-Year Experience Survey	2,422 first-year students	15	17.4	32.4
	Baik et al. (2015)	8 universities	2014 First-Year Experience Survey	1739 first-year students	15	18	33
Asia							
China	Guo (2014)	50 universities	Follow-up Survey of College Graduates in China	6,977 students	NA	13.4	NA

Relationship between Time Allocation and Student Outcomes

Studies have also examined the relationship between time investment and student academic outcomes. In the US, for instance, Stinebrickner and Stinebrickner (2008) analysed longitudinal survey and administrative data on 210 undergraduate students, using instrumental variable estimation. They found that one additional hour of studying per day increased first-semester GPA by 0.36 points, and that a decrease of about forty minutes in study time per day decreased GPA by 0.24 points. The authors concluded: "simply increasing effort, even without refining study techniques, could make a substantial difference in academic outcomes" (p. 19). Brint and Cantwell (2010) analysed data on 6,300 survey participants across eight campuses of the University of California System, using regression methods. They found that one additional hour invested in academic activities (lecture/study time) was associated with an increase of 10% of a standard deviation in GPA and 23% of a standard deviation in academic conscientiousness. Arum and Roksa (2011) used longitudinal survey data and administrative records on 2,322 undergraduate students from 24 US universities. Using regression analysis to examine gains in learning, they found that an increase in self-study time was associated with an increase in gains in critical thinking, reasoning and writing skills.

Studies conducted outside the US context have also established the link between time allocation and academic outcomes. Dolton, Marcenaro and Navarro (2003) used survey data and administrative records on 1,976 students at the University of Malaga (Spain) to examine the relationship between student time allocation and first-semester exam performance. Using stochastic frontier, instrumental variable, and value added models, they found that the impact of class attendance time was four time more important than that of self-study time. They attributed this unusual finding to the fact that in Spanish higher education "[a] lot of time is spent in lectures and classes in instruction and practice for the examinations by working through past examination papers" (p. 553).

Meng and Heijke's (2005) used survey data on 18,532 graduates from nine European countries. Using a stochastic frontier model, they found that time spent attending classes had a positive impact on the acquisition of discipline-specific competencies, whereas time spent on self-study had a positive impact on the acquisition of both discipline-specific and generic competencies.

Grave (2011) used multiple years of survey data on 11,297 students at seventeen universities and technical colleges in Germany to examine the impact of time allocation on undergraduate students' grade performance. Using regression and stochastic frontier models, the study found that time spent attending classes was positively associated with overall grades for female students, high-achieving students, and social sciences and sciences/engineering students. Self-study time was found to be associated with overall grades for male and female students, high and low ability students, and students in art/humanities and social sciences. An increase in class attendance time, self-study time, and time spent on other study-related activities by 1% was found to increase grades by 0.01%.

Bratti and Staffolani (2013) used survey data on 370 first-year undergraduate economics students at Marche Polytechnic University (Italy), to examine the effect of time use on undergraduate academic performance. They used a two-step maximum likelihood estimation to deal with endogeneity and found that time allocation was an important predictor of students' academic performance. Their results indicate that time allocated to lecture attendance had an important positive effect on academic performance only in quantitative courses, whereas self-study time had an important positive effect on performance in all courses. They found that a 1% increase in lecture attendance increased grades by 0.06% to 0.09% in quantitative courses; a 1% increase in self-study time increased grades by 0.08% to 0.12% in all courses.

Masui and his colleagues (2014) used data on 168 freshmen enrolled in 14 courses in Business Economics at Hasselt University in Belgium, to examine the relationship between study time and academic performance. Using OLS regression, they found that students who invested more study time also had better exam performance in most courses. Guo (2014) used survey data on 6,977 students at 50 universities in China. Among other things, he used regression analysis to examine the relationship between study time and academic performance. He found that hours spent studying out of class per week was positively associated with the average course score.

Study Purpose and Research Questions

The purpose of this study is to examine the gap between the amount of time students allocate to academic activities and the amount they are expected to allocate to such activities based on academic credit standards. The study examines two research questions:

(1) To what extent does the amount of time students allocate to academic activities deviate from standard ECTS and Carnegie expectations?

(2) To what extent does the gap (or discrepancy) between actual and expected time allocation impact undergraduate students' academic performance?

Data and Methods

Data Sources and Sample Description

Data for this study come from surveys administered to first-year and final year undergraduate students from 2016 to 2018 at Nazarbayev University (NU). The study institution, an elite public research university in Kazakhstan, integrates Western, Central Asian, and ex-Soviet educational standards (Seidimbek, 2013). Its academic programs were established through unique strategic partnerships with some of the top-ranked universities in the world. The University uses English as its medium of instruction. Its students are recruited through a competitive process among secondary school students in Kazakhstan and are fully funded through government scholarships. In 2017, NU had over 4,200 students (61% undergraduate, 21% graduate, and 18% preparatory) and about 450 professors (78% expatriates).

The sample for this study includes 2,232 first-year and fourth-year undergraduate students who participated in the surveys. Response rates averaged 57% for first-year and 71% for final-year students over a three-year period. These surveys constituted the data source for the number of hours per week allocated to out-of-class study and the number of class sessions missed during the term. Additional data, including academic and demographic information, were obtained from University databases. Table 2 provides descriptive statistics on the sample.

Table 2. Descriptive statistics on study participants

	Mean	Stand. Dev.	Minimum	Maximum	N
Dependent variable					
Term GPA	3.05	0.62	0.00	4.00	2,232
Treatment					
ECTS time allocation gap (in %)	35.29	21.20	-106.00	75.50	1,990
Carnegie time allocation gap (in %)	28.10	23.56	-128.89	72.78	1,990
Control Variables					
Male student	0.49	0.50	0	1	2,232
Age at admission	17.66	0.77	15.77	34.94	2,232
First-year student	0.52	0.50	0	1	2,232
Fourth-year student	0.48	0.50	0	1	2,232
Perfect secondary school GPA	0.59	0.49	0	1	2,197
Attended Kazakh-Turkish secondary school	0.27	0.45	0	1	2,232
Attended Nazarbayev Intellectual	0.30	0.46	0	1	2,232
Attended other secondary school	0.42	0.49	0	1	2,232
Entry-level English proficiency (overall IELTS score)	6.40	0.62	5.00	8.50	2,211
Direct entry (no preparatory program participation)	0.12	0.32	0	1	2,232
Engineering major	0.27	0.45	0	1	2,232
Humanities and social science major	0.29	0.45	0	1	2,232
Science and technology major	0.44	0.50	0	1	2,232
Cumulative GPA in previous semester	3.05	0.53	0.67	4.00	2,226
Number of ECTS credit enrolled	30.15	4.66	6	42	2,232
Frequency of academic behavior (composite score)	39.46	15.78	0	100	2,015
Level of difficulty encountered (composite score)	38.94	15.99	0	100	1,973
Self-concept (composite score)	67.65	20.55	0	100	1,920
Dependency on others (composite score)	45.44	19.46	0	100	1,920
Stress level (composite score)	49.91	20.27	0	100	1,908
Self-esteem (composite score)	69.99	22.16	0	100	1,907

Variables

The dependent variable was students' term Grade Points Average (GPA) and was measured on a scale from 0 to 4. The treatment variable was overall time allocation gap, expressed as the degree to which the total amount of time invested in academic activities (class attendance and out-of-class study time) fell short of the expected number of hours, given the student's credit load. This measure was first expressed in percentages, ranging from negative to positive values—with negative values meaning that actual time exceeded standard expectations and positive values meaning that actual time fell short of expectations. Students were then classified into four quartiles/groups based on the magnitude of the time allocation gap relative to other students in the same cohort. The treatment group included students in the bottom quartile of time allocation gap (i.e., those with the smallest gap). This group included diligent students whose actual time allocation was closest to or matched the amount of time students were expected to allocate. Comparison groups included students in each of the upper time allocation gap quartiles. Time allocation gap was computed based on both ECTS and Carnegie standards. The study included various control variables, including:

- Demographic characteristics: gender, admission age, and class level
- Academic preparation: type of secondary school attended, secondary school GPA, entry-level English proficiency, and whether or not the student completed a preparatory program before undergraduate admission
- Academic experience in college: field of study, term credit load, level of difficulty encountered, and frequency of academic behaviours
- Psychological measures (composite measured based on a series of survey items): self-confidence, self-esteem, dependency on others, and stress level

Some variables had missing data. Psychological measures, for instance, had around 15% of missing values. Hot-deck imputation was used to impute missing values via a Statistical Program for the Social Sciences (SPSS) macro developed by Myers (2011).

Study Design: Propensity Score Matching

The study used propensity score matching (Rosenbaum, 1991, 2010; Rosenbaum & Rubin, 1983; Rosenbaum & Rubin, 1984) to address self-selection bias—due to the fact that students who allocate more time to academic activities may differ systematically from those who allocate less time to such activities. Propensity score matching, as Schneider and his colleagues (2007) observed ''[addresses] an important issue in empirical research, namely, estimates of effects for certain groups when randomization is not possible, and where sample elements have self-selected themselves into treatment or control conditions'' (p. 50).

The study used the following analytical procedures. First, logistic regression was used to estimate the probability of being in the lowest (rather than an upper) quartile of the time allocation gap, as a function of student characteristics. Only variables measured before the students' time allocation decision in the semester of interest were included as predictors: demographic characteristics, academic preparation, cumulative GPA at the end of the previous semester, undergraduate field of study, and the number of semester credit hours enrolled. Second, these predicted probabilities were used to match students in the treatment condition (being in the lowest quartile of time allocation gap) to one or more students in the control condition (being in an upper quartile of time allocation gap). This procedure known as full matching (Rosenbaum, 1991) has been found to yield better covariate balance compared to procedures that match each unit in the treatment condition to only one unit in the control condition (Gu & Rosenbaum, 1993). Third, after matching, covariate balance was assessed using *the standardized difference in percent* (Rosenbaum & Rubin, 1985) and histograms (Ho, Imai, King, & Stuart, 2011). Matching procedures were implemented in the R statistics software (R Core Team, 2013), using the MatchIt package (Ho, Imai, King, & Stuart, 2007; Ho et al., 2011), with the *full matching* algorithm implemented via the *optmatch* package (Hansen, 2004).

Post-Matching Analyses

Ordinary Least Squares regression analysis was used to examine the difference in semester GPA between students in the treatment condition and those in the control condition. In addition to adjusting for the predictors used in the propensity score model, this analysis also adjusted for frequency of academic behaviours and psychological measures (which were not included in the propensity score model because they were measured at the same time as time allocation). Regression results were used to compute the Average Treatment Effect on the Treated (ATT) and the Average Treatment Effect on the Untreated (ATU), based on 1000 simulations. The ATT is the mean effect for individuals who actually were in the treatment condition (Wooldridge, 2002) whereas the ATU is the expected effect of the treatment condition on individuals who did not participate in the treatment/program (Moreno-Serra, 2007). Finally, sensitivity analysis was conducted to assess the robustness of the results. All post-matching analyses were implemented using the *Zelig* package (Imai, King, & Lau, 2007) in the R software (R Core Team, 2013), with the exception of sensitivity analysis which was conducted in the STATA software (StataCorp, 2015).

Results

Descriptive Results on Time Allocation

Descriptive results suggest that an average first-year student was enrolled in 31.5 ECTS credits and invested 33.6 hours per week in academic activities. An average fourth-year student was enrolled in 30.1 ECTS credits and invested 31.9 hours per week in academic activities. The ECTS time allocation gap was 35.8% for first-year students and 34.8% for fourth-year students. In other words, the amount of time that an average student allocated to academic activities fell short of ECTS standards by 35.8% for first-year students and 34.8% for fourth-year students. Under the Carnegie standards, these gaps were lower: 28.7% for first-year and 27.5% for fourth-year students respectively.

Under the Carnegie standards, it was possible to compute these gaps for class attendance and out-of-class study separately. Results suggest that first-year students allocated 5.8% less time to class attendance but 40.4% less time to out-of-class study than expected. Fourth-year students allocated 7.1% less time to class attendance but 38.9% less to out-of-class study than expected. These results suggest that the amount of time students allocated to lecture attendance was close to the expected amount. In contract, the amount of time allocated to out-of-class study deviated substantially from the expected amount.

Propensity Score Matching Results

Results of analyses conducted before matching revealed systematic differences in background characteristics between students who allocated more time and those who allocated less time to academic activities. Table 3 provides a summary of covariate balance, expressed in terms of *standardized difference in percent*. According to Rosenbaum and Rubin (1985), a covariate with an absolute standardized difference greater than 20% is problematic and needs analytical adjustment. In the unmatched samples, about 40% of the covariates had an absolute standardized difference greater than 20% under the ECTS time allocation model. In other words, treatment and comparison groups differed by more than 20% of a standard deviation along these covariates. Under the Carnegie time allocation model, 30% of the covariates had a standardized difference greater than 20%.

Table 3. Covariate Balance: Percent of Predictors at Different Levels of Standardized Difference in %

	ECTS Time Allocation Gap		Carnegie Time Allocation Gap	
Bias level	Unmatched Samples	Matched Samples	Unmatched Samples	Matched Samples
<= 10%	42.9	90.0	42.9	90.0
> 10% and <= 20%	18.6	10.0	27.1	10.0
> 20%	38.6	0.0	30.0	0.0

Note: This table summarizes the results of covariate balance across all 12 propensity score models used in this study: six models using the ECTS standards and six using the Carnegie standards (within each system, analyses were conducted for first-year and final year students separately and compared students in the bottom quartile of time allocation gap to those in each of the three upper quartiles).

After matching, however, covariate balance improved substantially. In the matched samples, there was no covariate with a standardized difference greater than 20%. In fact, 90% of the predictors had a standardized difference less than 10%, which implies that treatment and comparison groups became much more similar on background characteristics and also more comparable. Figure 1 further provides an illustration of covariate balance in raw and matched data for fourth-year students in bottom and top quartiles of ECTS time allocation. In the raw data, the distribution of propensity scores for students in the treatment group differed substantially from that of students in the control group. After matching, however, the two distributions were very similar.

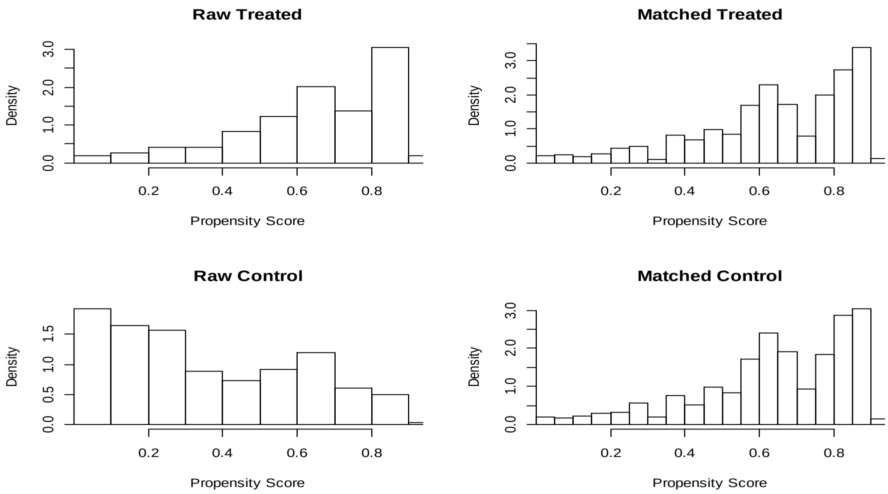

Figure 1. Example of covariate balance between fourth-year students in bottom and top quartile of ECTS time allocation gap

Post-Matching Results

Post-matching regression results suggested that there was a relationship between time allocation gap and undergraduate academic performance. Table 4 summarizes regression results for first-year students and Table 5 regression results for fourth-year students.

Table 4. Post-Matching Regression Results for First-Year Students

Treatment Group	Comparison Group	ECTS Standards	Carnegie Standards	N
1st quartile	2nd quartile	0.07 (0.05)	0.07 (0.13)	552
1st quartile	3rd quartile	0.20 (0.05)***	0.23 (0.05)***	545
1st quartile	4th quartile	0.24 (0.05)***	0.26 (0.05)***	550

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Standard errors are shown in parentheses. All post-matching regression models controlled for Gender, admission age, secondary school GPA, type of secondary school attended, entry-level English proficiency, direct admission (as opposed to admission through the preparatory program), undergraduate study field, cumulative GPA in previous semester, number of credits enrolled, frequency of academic behaviors, self-concept, self-esteem, dependency on others, and stress level.

Table 5. Post-Matching Regression Results for Fourth-Year Students

Treatment Group	Comparison Group	ECTS Standards	Carnegie Standards	*N*
1st quartile	2nd quartile	0.05 (0.04)	0.07 (0.04)	515
1st quartile	3rd quartile	0.14 (0.05)**	0.15 (0.05)**	509
1st quartile	4th quartile	0.18 (0.06)***	0.23 (0.06)***	517

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Standard errors are shown in parentheses. All post-matching regression models controlled for Gender, admission age, secondary school GPA, type of secondary school attended, entry-level English proficiency, direct admission (as opposed to admission through the preparatory program), undergraduate study field, cumulative GPA in previous semester, number of credits enrolled, frequency of academic behaviors, self-concept, self-esteem, dependency on others, and stress level.

Students in the bottom quartile of time allocation gap (i.e., those whose actual time investment was closest to the expected amount) had higher term GPA compared to their counterparts in the third and fourth quartiles of time allocation gap, after adjusting for background characteristics. The difference was statistically significant, and this pattern of results was consistent for first and second-year undergraduate students regardless of whether time allocation gap was computed using ECTS or Carnegie standards.

Table 6 and Table 7 provide estimates of the average treatment effect on the treated (ATT) and the average treatment effect on the Untreated (ATU) for first-year and fourth-year students respectively. Treatment effects were estimated based on 1,000 simulations and based on regression results. Treatment effects were negligible when students in the first quartile of time allocation gap were compared to those in the second quartile. However they were significant and meaningful when students in the bottom quartile were compared to those in the third and fourth quartiles. For first-year students in the first quartile of time allocation gap (Table 6), for example, ATT values suggest that being in the first rather than fourth quartile of time allocation gap was associated with a term GPA increase of 24 percentage points under ECTS standards and 27 percentage points under Carnegie standards. ATU values for the same group suggest that if students who were in the fourth quartile of time allocation gap had actually been in the first quartile, their gain in GPA would have been similar to the gain made by students in the first quartile (i.e., 24 percentage points). This is because ATT and ATU values were practically equal. This pattern of results is consistent with fourth-year students, although ATT and ATU values for this group were slightly smaller compared to those observed for first-year students.

Table 6. Average Treatment Effects for First-Year Students

Time allocation Gap Quartiles		ECTS Standards		Carnegie Standards	
Treatment Group	*Comparison Group*	*ATT*	*ATU*	*ATT*	*ATU*
1st quartile	2nd quartile	0.07 (0.05)	0.07 (0.05)	0.07 (0.05)	0.07 (0.04)
1st quartile	3rd quartile	0.20 (0.05)***	0.19 (0.05)***	0.22 (0.05)***	0.23 (0.05)***
1st quartile	4th quartile	0.24 (0.05)***	0.24 (0.05)***	0.27 (0.05)***	0.26 (0.05)***

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Standard errors are shown in parentheses.

Table 7. Average Treatment Effects for Fourth-Year Students

Time allocation Gap Quartiles		ECTS Standards		Carnegie Standards	
Treatment Group	*Comparison Group*	*ATT*	*ATU*	*ATT*	*ATU*
1st quartile	2nd quartile	0.05 (0.05)	0.05 (0.04)	0.07 (0.04)	0.07 (0.04)
1st quartile	3rd quartile	0.14 (0.05)**	0.14 (0.05)**	0.15 (0.05)**	0.15 (0.06)**
1st quartile	4th quartile	0.18 (0.05)***	0.19 (0.05)***	0.23 (0.06)***	0.23 (0.05)***

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Standard errors are shown in parentheses.

Figure 2 shows adjusted term GPA for first and fourth-year students, under ECTS standards. Results suggest that there was a clear (albeit small) difference in term GPA between students in the bottom quartile and those in the third and fourth quartiles of time allocation gap.

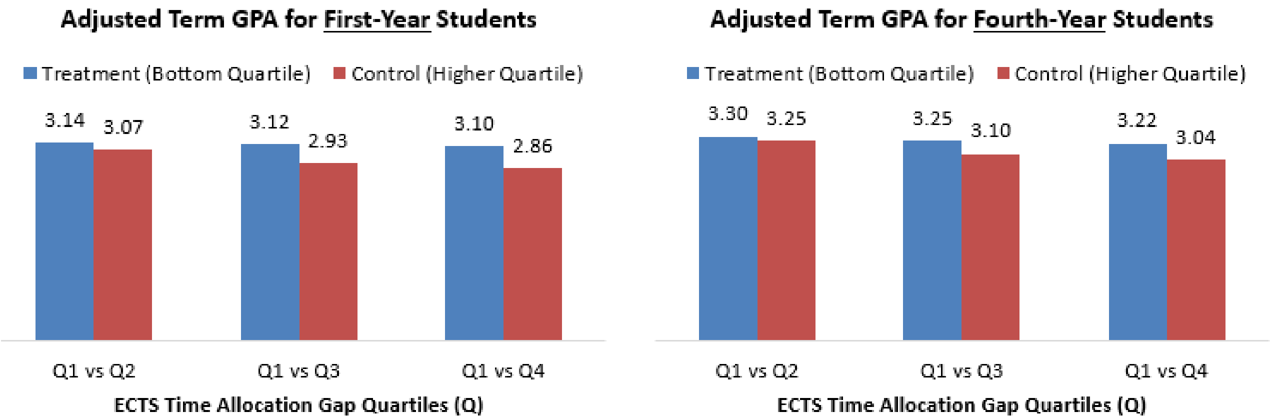

Figure 2. Adjusted Term GPA for Treatment and Control Groups under ECTS standards

Sensitivity Analysis

Propensity score matching can result in a biased estimator of the treatment effect, if a variable that affects both treatment assignment and the outcome variable of interest were to be omitted from the model (DiPrete & Gangl, 2004). For this reason, it was necessary to check how robust the estimated treatment effects would be in the presence of omitted variables. The study used Rosenbaum's (2002; 2005) approach for bounding treatment effects and implemented this technique using a STATA (StataCorp, 2015) package developed by Becker and Caliendo (2007).

Table 8. Values of the sensitivity parameter at which the treatment effect ceases to be significant

	First-Year Students		Fourth-Year Students	
	1st Quartile vs. 3rd Quartile	*1st Quartile vs. 4th Quartile*	*1st Quartile vs. 3rd Quartile*	*1st Quartile vs. 4th Quartile*
ECTS credit system	1.2	1.7	2.4	2.6
Carnegie credit system	1.3	1.7	2.4	3.0

Notes: Values of the sensitivity parameter at which the treatment effect ceases to be significant are expressed in terms of the odds of differential assignment to the treatment (vs. the control) condition due to unobserved factors. Sensitivity analysis was not conducted for first quartile vs. second quartile because the difference in academic performance between these two groups was not statistically significant.

Table 8 summarizes the results of sensitivity analysis and displays the value of the sensitivity parameter, Γ, at which the treatment effect would cease to be significant. Values of the sensitivity parameter represent a measure of the odds ratio for differential treatment assignment due to unobserved background characteristics. Sensitivity parameter values were lower for first year students and significantly higher for fourth-year students. When treatment is defined as being in the first quartile of time allocation gap (i.e., the most diligent group) as opposed to being in the third quartile, results suggest that the treatment effect would cease to be significant if an unobserved variable were to cause the odds ratio of treatment assignment to differ between treatment and control cases by a factor of 1.2 to 1.3 for first-year students and a factor of 2.4 for fourth-year students. When treatment is defined as being in the first quartile of time allocation gap (i.e., most diligent group) as opposed to being in the fourth quartile (least diligent group), results suggest that the treatment effect would cease to be significant if an unobserved variable were to cause the odds ratio of treatment assignment to differ between treatment and control cases by a factor of 1.7 for first-year students and a factor of 2.6 to 3 for fourth-year students.

In short, results are particularly robust against omitted variables for fourth-year students: an omitted variable would need to be a particularly strong predictor of both time allocation and academic performance in order to cause the estimated treatment effect to become insignificant. For first-year students, results are more robust when students in the first quartile of time allocation gap are compared to those in the fourth quartile and less robust when these students are compared to those in the third quartile.

Conclusion, Discussion and Implications

This study examined student time allocation in terms of the gap (or discrepancy) between the number of hours students allocated to academic activities and standard expectations from academic credit systems. One advantage of this approach is that it examines time allocation relative to the student's actual credit load. Findings from this study corroborate those from previous studies that focused on the number of hours allocated to academic activities (without consideration for academic credit standards). Consistent with findings from previous studies (e.g., James et al., 2010; McCormick, 2011), we found that undergraduate students do not invest as much time in academic activities as expected. More particularly we found that the average undergraduate student spent 35% less time on academic activities than expected under ECTS standards and 28% less time than expected under Carnegie standards. However, there were considerable differences among students. For instance, under ECTS standards, students in the bottom quartile of times allocation (most diligent students) allocated only 7% less time whereas those in the top quartile of time allocation (least diligent students) allocated 60% less time, on average, to academic activities. Under Carnegie standards, students in the bottom quartile of time allocation gap actually met or exceeded expectations whereas those in the top quartile of time allocation gap allocated 56% less time to academic activities than expected.

This study also examined the impact of time allocation on academic performance. Previous studies had found that the amount of time allocated to academic activities has a positive impact on academic performance (Bratti & Staffolani, 2013; Brint & Cantwell, 2010; Dolton et al., 2003; Grave, 2010; Stinebrickner & Stinebrickner, 2008). Our results are consistent with those of previous studies. We found that students whose time allocation was closest to the amount expected under academic credit systems experienced a positive and meaningful gain in GPA compared to their counterparts whose time allocation fell short, by a substantial margin (i.e., time allocation gaps in the third or fourth quartile), of standard credit expectations. The size of the effect ranged from 20% (Cohen's d = 0.20) to 33% (Cohen's d = 0.33) of a standard deviation, which corresponds to a small (but also meaningful) effect.

This finding raises a question regarding the role and importance of time investment in academic activities. Critics have rightly pointed out that the amount of time spent on task does not equal learning (Carnegie Foundation for the Advancement of Teaching, 2013; Harris, 2002; Shedd, 2003; Silva, 2013). However, this does not mean that time investment does not matter in the educational process. In fact, mastering a concept or acquiring a skill or competency requires that a student invest some amount of time in the process. The amount ("how much") and quality ("how well") of time that the student invests are separate questions. It is important to conceptualize time as an input in the education production function (Babcock & Marks, 2011; Dolton et al., 2003; Stinebrickner & Stinebrickner, 2008) and not as an outcome (or proxy for learning). As Babcock and Marks (2011) noted, there is "strong empirical evidence" that "studying is an important input to the production of knowledge, skills, and human capital" (p. 6).

One recommendation for academic institutions is to consider not just how much time students spend on academic activities but also the degree to which time investment matches standard expectations. There are various possible reasons why students invest less time than expected. It is possible that many students simply invest the minimum amount of time needed to be successful in college (Kuh, Kinzie, Schuh, & Whitt, 2010). It is also possible that instructor and program expectations for students are not of sufficiently high standards (Babcock & Marks, 2010; McCormick, 2011). Considering that time is an important input into the learning process, institutions, programs, and instructors may wish to:

(1) re-assess the amount and quality of academic work required of students, to ensure that the level of effort expected of students is truly proportional to the level and quality of the academic outcomes students are expected to achieve.

(2) clearly communicate learning outcomes to students and educate students on the amount and quality of effort students are expected to invest in order to reach these outcomes.

(3) use a variety of mechanisms (class time, advising, etc.) to educate students about time allocation and its relationship with academic outcomes.

Limitations

One limitation of the present study is that it measured time allocation retrospectively. Citing a number of studies, Brint and Cantwell (2010) observed that “retrospective accounts of time use are less accurate and reliable than accounts based on time diaries” (p. 2448). However, they also indicate that this limitation can be surmounted by providing students with a reference point they can use to estimate time allocation. In student surveys, we used “current academic year” as the reference point. In addition, we combined administrative and survey data, which may help reduce measurement error.

Another limitation is that propensity score matching only strives to achieve balance on observed covariates (Rubin, 2002)—unlike experimental design which achieves balance on both observed and unobserved covariates. Some scholars (DiPrete & Engelhardt, 2000) have shown that propensity score matching can also help reduce selection bias due to unobserved covariates. However, it is possible that the probability of having a small rather than large time allocation gap is related to some other student characteristics that were not included in the propensity score model. If such unobserved characteristics were to be correlated with academic performance, in addition to being correlated with time allocation, bias could be introduced in the estimation of the treatment effect. Sensitivity analysis conducted in this study suggests that an unobserved characteristic will need to be a powerful predictor of both time allocation and academic performance to alter the study’s conclusion of the impact of time allocation gap.

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