College internships and student academic outcomes: Immediately and dynamic effects

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by
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Dedication

This thesis work is dedicated to my parents and grandparents,
they are always my main support and source of inspiration.

Ariell Paladines G.

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DECLARACIÓN EXPRESA

"La responsabilidad del contenido de este Trabajo de Titulación, corresponde exclusivamente al autor, y al patrimonio intelectual de la misma **ESCUELA SUPERIOR POLITECNICA DEL LITORAL**"

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Abstract

This work examines the effect of internships on academic outcomes, academic performance and number of credits selected, using a panel dataset from a public university in Ecuador. My approach consists of a difference-in-differences design in which I use a new estimator robust to heterogeneous and dynamic effects. The treatment consists of whether a student takes an internship program during his or her semester of classes. The results indicate that, on average, internships have a positive effect on students' academic performance of approximately 0.27 academic points (3.8% of academic performance mean). The evidence suggests that internships during class break are the best option for academic outcomes, since they have a greater average aggregate effect on academic performance and, although they decrease the number of credits selected, it is less than when internships are taken during classes. These results are robust across several specifications. In summary, as a policy alternative, the results suggest that it is preferable to take programs of this type in periods when students do not have to spend their time taking class hours.

Keywords: Internships, academic performance, education policy, two-way fixed effects, differences-in-differences

JEL Codes: C51, I21, I23, I28

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1 Introduction

Internships during college are now a common occurrence at many universities worldwide. Internships are generally one-time work experiences that are related to the professional goals of university students. In these programs, students generally work in professional settings under the supervision of professionals in the field. In addition, internships are considered increasingly important as a way to gain experience and improve job search results and labor market outcomes after college graduation (Silva et al., 2015; Geel and Backes-Gellner, 2012). In Ecuador, the Organic Law of Higher Education (2010)[1] indicates that, as a prerequisite for obtaining the academic degree, students must accredit community service through community outreach projects and pre-professional internships with appropriate pedagogical support, in the areas of their specialty. This law obliges students to take pre-professional internships during their university career, therefore, they are faced with several decisions, among these, the allocation of their time between study hours or internship hours, which may have implications on their academic results.

In recent years, college employment has become more of an issue as students work at a higher rate and for longer hours during their studies. These results may be due primarily to changes in demographics, rising tuition costs and economic conditions (Scott-Clayton, 2012).

The seminal work in the field relating college employment and academic outcomes is that of Ehrenberg and Sherman (1987) using a structural model, who find that work during college has a marginal negative impact on grades and increases the probability of dropping out. Empirically, several authors have found that the effect of employment during college is insignificant, but that there is a negative effect on the time to graduation (Darolia, 2014; Häkkinen, 2006; Triventi, 2014). On the other hand, studies such as that of Scott-Clayton and Minaya (2016) find that the number of hours students spend working, within work programs that allow them to study and work at the same time, does have a positive effect on grades, while Stinebrickner and Stinebrickner (2003) suggests that working during the first semester has a negative impact on academic performance. Besides, Passaretta and Triventi (2015) mention that work experience during college helps employability in the short term after graduation, and, that if the work experience is related to the student's college career, it decreases the likelihood that the student's future job will be unrelated to his or her college career.

However, as pointed out by Routon and Walker (2019), there are a greater number of studies measuring the effects of college employment than those measuring the effects of internship programs. Siedler et al. (2016) and Nunley et al. (2016) analyze the long term effects of these programs and find that internships increase wage premiums after graduation and increase the number of job opportunities for those who took them. For the short term, academic studies are even less important. In this line, Routon and Walker (2015, 2019) find internships to have positive effects on student academic performance.

[1] Url: https://www.ces.gob.ec/documentos/Normativa/LOES.pdf

In this context, the main objective of this paper is to examine the effect of internships on students' academic outcomes within the university. Specifically, this paper aims to determine the immediate and dynamic effect of internships on students' academic performance and number of credits selection. In addition, this paper examines whether the effect is heterogeneous between those who allocate all of their class semester time to internships and those who take internships partially in the semester. Moreover, this paper aims to determine whether taking internships during class break periods has a significant effect on students' academic results and works as an alternative to taking internships during classes. Finally, the paper analyzes the heterogeneity that may exist between paid and unpaid internships to determine whether this incentive has any additional effect on the academic performance of students.

I used a panel dataset comprising of the students' academic results at Escuela Superior Politécnica del Litoral (ESPOL) , a public university in Ecuador, between 2007 and 2017. My approach consists of a generalized difference-in-difference (DiD) design, where the treatment consists of whether students take their internships in a specific semester. Considering the recent literature, which indicates that the use of the traditional Two-Way Fixed Effects (TWFE) estimator in designs where different groups or individuals are exposed to the treatment at different times, and, treatment is staggered or take-it-and-leave-it, could lead to biased effects (Callaway and Sant'Anna, 2020; Sun and Abraham, 2020; Goodman-Bacon, 2018; de Chaisemartin and D'Haultfœuille, 2020a). This paper takes a different approach and estimates the desired effect using a new differences in differences estimator proposed by de Chaisemartin and D'Haultfœuille (2020b) , which is robust to heterogeneous and dynamic effects.

The main challenge to overcome in identifying this type of causal effect is student selection bias. Thus, in order to have a reliable estimate, I use a placebo test that allows me to check that, in the absence of the internship, students who took the internship would have experienced changes in their academic outcomes similar to students who did not take these programs.

My results show that, on average, internships during class have a positive effect on students' academic performance of approximately 0.27 academic points (3.8% of academic performance mean). However, I also estimate heterogeneous effects between those who take internships during their entire class semester time and those who take them partially, and , between those who take paid internships and those who are unpaid. These results indicate that partial and unpaid internships have a larger positive effect of about 0.24 and 0.42 academic points on academic performance (3.4% and 5.9% of academic performance mean) , respectively, than to programs that are take during class or are paid. As an alternative, taking internships during class break has a larger positive effect on academic performance, which is around 0.34 points (4.8% of academic performance mean). These results are robust to specifications that include student college fixed effects and interaction terms between student department and semesters.

The rest of the paper is structured as follows: Section 2 is a brief about institutional background, Section 3 and Section 4 describes the dataset and empirical design , Section 5 presents the results, and Section 6 concludes.

2 Institutional Background

The internship program analyzed corresponds to those offered at ESPOL. At this university, there are two types of internships,social service [2] and pre-professionals,but, in this document, I work with pre-professional internships. Pre-professional internships are learning activities through which undergraduate students apply the knowledge acquired in their careers and develop specific skills and abilities for a good performance of their future profession, and, at ESPOL, internships are a prerequisite for obtaining a professional title. Students must accredit at least 400 hours of pre-professional internships articulated to the career profile because the conditions established in the Academic Regime Regulations, issued by the Council of Higher Education (CES). These internships are carried out in organizational, institutional, business, community, or other environments related to the professional field of the career, public or private, national or international.

For preprofessional internships' execution, the signing of an internship agreement with the host company or institution is verified. The agreements between host companies and students will state the nature of the legal relationship, the internship planned activities, duration, and the commitments of the parties. Commitment letters must be signed by the highest authority of the student academic department, the teaching tutor, the company tutor, and the company representative. Internships can be paid or unpaid, depending on the contract made between students and the offering companies. If the internship is paid, it is governed by the applicable regulations without modifying the academic effects described above. Professional internships are distributed throughout the career and before students taking the capstone project to get the undergraduate title. Students may begin their internships when they complete the required courses for the internship they select.

Students can do up to 30 hours a week of pre-professional internships, as long as these do not exceed 55 hours per week of total workload for a university student, considering the hours of theoretical, practical, and autonomous learning. In case internship' characteristics demand it and the coordinator of preprofessional internships of the career, college, or university authorize it, students can carry out work activities on weekends or have a workload greater than 30 hours per week. Likewise, ESPOL's regulation allows students who carry out preprofessional internships abroad, can register these hours of work as hours of professional internships.

According to ESPOL's internal regulations and the CES , there are other activities that can be considered as professional internships: research and teaching assistantships . Students can support

[2] Social service internships are aimed at caring for people or groups in vulnerable contexts, through institutional outreach programs and community service projects and activities.

the research assistantship in data collection and processing activities, among other activities, according to the researcher's indications. Research assistantships are carried out within research projects approved by the Institution and are recognized for 80 hours of total professional practices. However, in this research, this type of activity is not considered as an professional internship.

3 Data

For my analysis, I use administrative data from the Department of Information Systems and Technology Management (GTSI for its acronym in Spanish) at ESPOL. I obtain a panel data of students' academic performance [3] registered at ESPOL for the academic years 2007 to 2017 by semester. Academic and sociodemographic data are extracted from the GTSI database, while internships' data come from the Department of Relations with Society at ESPOL, and indicate the academic period in which students have done their internships. Using these data, I tracked students' academic progress by semester, including semester academic performance, number of credits in which they enrolled, and internships' status, that is an indicator that shows whether a student have taken an internship or not in an specific date [4].

In addition to the sociodemographic variables that work as explanatory variables, I control for other external factors that could affect the relationship between the student decision about take an internship and their academic performance, in particular, a change occurred in the regulation of internships. Prior to 2015, the ESPOL Social Department was solely responsible for monitoring and managing students' professional internships, regardless of the academic college to which they belonged. Finally, is important to know that, since 2015, each academic college is responsible for the administration and monitoring related to all stages of the process of students' professional internships, besides, each academic college designate a person in charge, as well as tutors and project directors. Therefore, this change is included in our econometric specifications set forth below.

In this study, I only consider students who enrolled since 2007, since I did not have information for those who enrolled in previous years. As a result, my sample contains 19,524 students in 9 faculties for a total of 148,321 observations. On average, in my sample, the students' semesters number at the institution is approximately 6, although this number ranges from a minimum of 1 semester to a maximum of 22 semesters. Besides, on average, the 6 percent of the semesters the students take an internship. Regarding to sociodemographic characteristics, 58.8 percent of the students are male. Approximately 70 percent of my sample comes from Guayaquil (the city where

[3] At ESPOL, the academic performance ranges from 0 to 10, where 0 is a bad grade and 10 is the best.

[4] The academic data is structured at the level of the student selected subject, that is, the data observations represent the grades obtained from each student in all the subjects selected in the corresponding semester. Therefore, to obtain a single observation per student at the semester level, the average of all their grades is calculated, which is commonly known as academic performance or Grade Point Average by semester, and the sum of the number of credits by subject selected

the university is located) and the remaining 30 percent from other cities in Ecuador.

Table 1 presents summary statistics for the outcome and the remaining explanatory variables in my sample. These outcome variables include GPA and number of credits . All of the variables are shown for the full sample.

Table 1: Descriptive Statistics – Students

Variables	Mean	St.Dev	Min	Max
Outcome				
Academic performance	7.07	1.43	0.00	10.00
Number of credits	12.30	4.09	4.00	27.00
Explanatory				
Number of semesters	5.51	3.61	1.00	22.00
Internship status	6.40	24.50	0.00	100.00
Sociodemographic				
Gender				
Female	41.20	49.20	0.00	100.00
Male	58.80	49.20	0.00	100.00
Type of school				
Private	68.40	46.50	0.00	100.00
Public	28.40	45.10	0.00	100.00
Mixed	3.10	17.40	0.00	100.00
Provenance				
Guayaquil	68.70	46.40	0.00	100.00
Obersvations		148321		
Students		19524		

Note : The internship status variable and sociodemographic variables are expressed as percentages. All variables have 148321 observations.

4 Empirical Design

At ESPOL, all students are required to complete internship hours to achieve their degree, however, the decision of when to complete them is up to them. The beginning of any internship obeys the students' benefit maximization behavior in the academic context, which is mainly determined by the attainment of their degree, therefore, as the semesters go by, students tend to take their internship hours. However, there are other determinants that may also explain the timing of when students take their internships, but which are not directly observable.

Certainly, students' timing decision about whether to do an internship is not random. Had the decision to take an internship been random, the internship treatment effect could easily be estimated by the difference between the mean outcome of students who do an internship and those who do not. Nevertheless, any outcome differences between these two groups can not be fully attributed to the internship, even after controlling for observables, because there may be other factors that are related to academic outcomes and the student's decision to do an intern in a specific period. Therefore, to distinguish the effect of the internships from confounding factors, I need a suitable counterfactual: the average academic outcomes of the students who took an internship should they had not taken it.

Despite my data consist of a panel, in which I could apply a traditional two-way fixed effects (TWFE) regression model, in my study context, this is not a good option. In my panel, students who take the treatment do not necessarily keep it until the final period and can switch on or switch off the treatment in the period of their choice. Thus, it is plausible that there is a potential heterogeneous effect across students (groups) or periods, therefore, the results of the TWFE regression models are not reliable (Borusyak and Jaravel, 2017; Callaway and Sant'Anna, 2020; de Chaisemartin and D'Haultfœuille, 2020b; Goodman-Bacon, 2018; Sun and Abraham, 2020). I illustrate the TWFE results in my regressions estimating the simple non-dynamic form of the equation 1 by OLS in Appendix (see Table 6).

In addition, the internship program of a student at a specific semester may have an effect on that student's specific semester outcome, but it may also have an effect on its future outcomes. A commonly-used method to estimate this effect is to regress the outcome on groups or individual fixed effects, time fixed effects, the contemporaneous treatment, and lags of the treatment, commonly known as an event-study regression proposed by Autor (2003). Nonetheless, Schmidheiny and Siegloch (2020) and Sun and Abraham (2020) have shown that the event-study regression is also not robust to heterogeneous or dynamic effects.

To identify the desired effect, I exploit the student variation when taking an professional internship induced by the fact that, at ESPOL, there is no mandatory semester in which students have to do their internships; they can decide when to do it , how many internships take it and, although there is a certain minimum number of professional internship hours, the students can decide how long it last, that is to say, the students can switch on and switch off the treatment.

I use a generalized differences-in-differences (DID) research design that considers whether there is a change in academic outcomes for students who take an internship program compared to those who do not yet, in which the identification assumption implies that in the absence of the treatment, academic outcomes of the two groups should be the same. Instead of applying the traditional estimation methods, I employ the new DID estimator developed by de Chaisemartin and D'Haultfœuille (2020a,b), that, as the event-study regressions, this estimator relies on the standard common trends assumption, but unlike them, it is robust to heterogeneous and dynamic effects, and, it is applied to designs where groups can switch on and off of the treatment.

4.1 Econometric Setup

Formally, my empirical research design is a generalized DID design with a treatment status that can switch on and switch off. Therefore, in order to capture the instantaneous and dynamic effects of the internships on students' academic outcomes, I specify the following specification:

$$Y_{ist} = \alpha_i + \lambda_t + \sum_{\ell=-4}^{3} \beta^{\ell} Intern_{it} + \delta_{st} + \mu_{ist} \tag{1}$$

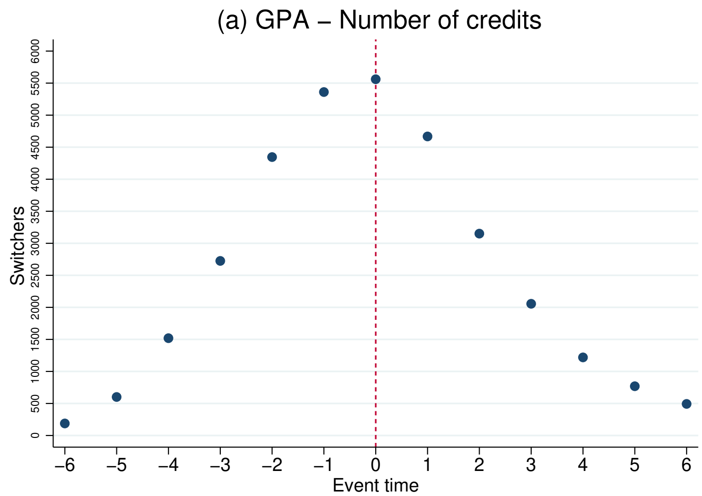
where Y_{ist} is a variable reflecting outcome for student i in college s in semester t. This outcome variable represents the students' academic outcomes. $Intern_{it}$ is the treatment variable that equals to one if student i took an internship during semester t. α_i control for student fixef effect and λ_t control for time fixed effect of the semester for the student. δ_{st} is a variable representing the student's academic college s in semester t. Specifically the estimator that I use to identify these treatment effects is the new differences-in-differences estimator proposed by de Chaisemartin and D'Haultfœuille (2020b). In addition, in columns 2, 3, 5 and 6 of results tables I also include the fixed effects of the college by semester, to allow students in different faculties of the university to follow different trajectories and take into account the differential shocks by faculties over time. Robust standard errors are clustered at the individual level.

The treatment effects that we are looking for are captured by β^{ℓ}, where ℓ represents the lags of treatment and let estimate the instantaneous and dynamic effects. Specifically, the new DID estimator that is used in this work identifies the treatment effect on the groups that take the treatment for the first time (switchers) at the time they switch. For every t and ℓ, this new estimator forms a DID estimator comparing the $t - \ell - 1$ to t academic outcome evolution, in groups treated for the first time in $t - \ell$ and in groups untreated from period 1 to t. Besides, with this new estimator is possible to capture the aggregate average effect of the estimated coefficients β^{ℓ} , the instantaneous and dynamic treatment effects, taking into account that the groups can switch off the treatment in any period and take it more than once.

Turning to the number of switchers that identify the various dynamic and placebo treatment effects , I present Figure 1 , which show the number of switchers, that are the number of students that take an internship, and let identify the treatment and placebo effects in my data. Importantly, I estimate dynamic effects up to 3 semesters after the first switch and estimate placebo effects up to 3 semesters before the first switch since the number of switchers falls more sharply after these periods, both for future effects and for placebo effects. Figure 1 reveals that the instantaneous treatment effect on GPA and number of credits is based on 5561 switchers, while the dynamic effect after 3 semesters is based on 2056 switchers.

Following de Chaisemartin and D'Haultfœuille (2020a), below I show the definition of this new estimator that is applied in my DID research design. First, is important to know some implicit definitions that were used in the development of the estimator. Let $N^1_{t,\ell} = \sum_{g:F_{g,1=t-\ell}} N_{g,t}$

Figure 1: Number of switchers for estimations



Note: The vertical lines represent the time when students first time switch on the treatment.

represent the number of observations in groups treated for the first time at period $t-\ell$, and, let $N_t^{nt} = \sum_{g:F_{g,1}>t} N_{g,t}$ represents the number of observations in groups untreated from period 1 to t. Likewise, $N_t^{\alpha t} = \sum_{g:F_{g,0}>t} N_{g,t}$ denote the number of observations in groups treated from period 1 to t, and, $N_{t,\ell}^0 = \sum_{g:F_{g,0}=t-\ell} N_{g,t}$ represents the number of observations in groups untreated for the first time at period $t-\ell$. The DID estimator that captures the instantaneous and dynamic effects is a weighted sum between the estimator of the effect of taking the treatment , $DID_{+,\ell}$, and the effect of taking it off, $DID_{-,\ell}$. These expressions look as follows:

$$DID_{+,t,\ell} = \sum_{g:F_{g,1}=t-\ell} \frac{N_{g,t}}{N_{t,\ell}^1}(Y_{g,t} - Y_{g,t-\ell-1}) - \sum_{g:F_{g,1}>t} \frac{N_{g,t}}{N_t^{nt}}(Y_{g,t} - Y_{g,t-\ell-1}) \tag{2}$$

and,

$$DID_{-,t,\ell} = \sum_{g:F_{g,0}>t} \frac{N_{g,t}}{N_t^t}(Y_{g,t} - Y_{g,t-\ell-1}) - \sum_{g:F_{g,0}=t-\ell} \frac{N_{g,t}}{N_{t,\ell}^0}(Y_{g,t} - Y_{g,t-\ell-1}) \tag{3}$$

Therefore, the robust DID of instantaneous and dynamic effects is :

$$DID_\ell = w_+^\ell DID_{+,\ell} + (1-w^\ell)DID_{-,\ell}, \tag{4}$$

where ℓ represents the lags of the treatment and w^ℓ is a weight proportional to the number of observations $DID_{+,l}$ applies to.

The aggregate average effect on the outcome is constructed with a weighted averages of the $DID_{+,t,\ell}$ and $DID_{-,t,\ell}$ estimators. However, without a staggered adoption design, some groups treated for the first time in $t-\ell$ may remain treated till t, while other groups may go back to the untreated status. Hence, DID_ℓ may estimate a mixture of different treatment effects. Thus, this estimator needs to one more equation to be robust. That equation is as follow:

$$DID^D_{+,t,\ell} = \sum_{g:F_{g,1}=t-\ell} \frac{N_{g,t}}{N^1_{t,\ell}}(D_{g,t} - D_{g,t-\ell-1}) - \sum_{g:F_{g,1}>t} \frac{N_{g,t}}{N^{nt}_t}(D_{g,t} - D_{g,t-\ell-1}), \tag{5}$$

where, given the definition of $F_{g,1}$, the previous equation simplifies to :

$$DID^D_{+,t,\ell} = \sum_{g:F_{g,1}=t-\ell} \frac{N_{g,t}}{N^1_{t,\ell}} D_{g,t}, \tag{6}$$

and $DID^D_{+,t,\ell}$ is a DID estimator similar to $DID_{+,t,\ell}$ except that the outcome is replaced by the treatment and take into account the number of treatments that groups have switched on.

Finally, to aggregate a robust average effect, the estimator is the ratio of weighted averages of the DID_ℓ and DID^D_ℓ estimators. This estimator looks as follows:

$$\hat{\delta} = \frac{\sum_{\ell=0}^{L_{nt}} w, \ell DID_\ell}{\sum_{\ell=0}^{L_{nt}} w, \ell DID^D_\ell} \tag{7}$$

where L_{nt} denote the number of time periods between the earliest period at which a group goes from untreated to treated and the last period at which a group has been untreated all along. Finally, this estimator captures the average effect of first switches on the outcome , discounted by the average effect of first switches on the treatment.

4.2 Identification Assumption

The main identifying assumption is that in the absence of the internship, adopting internship students would have experienced changes in academic performance and number of credits similar to non-adopting students.

To test the plausibility of this assumption, I use the long-difference placebo estimator proposed by de Chaisemartin and D'Haultfœuille (2020a). This estimator test if common trends holds over several periods, while the common use short-difference ones only test if it holds over pairs of consecutive periods. Then, the long-difference placebos may lead a more powerful test of commond trends. This new estimator looks as follows:

$$DID^{pl}_{+,t,\ell} = \sum_{g:F_{g,1}=t-\ell} \frac{N_{g,t}}{N^1_{t,\ell}}(Y_{g,t-2\ell-2} - Y_{g,t-\ell-1}) - \sum_{g:F_{g,1}>t} \frac{N_{g,t}}{N^{nt}_t}(Y_{g,t-2\ell-2} - Y_{g,t-\ell-1}). \tag{8}$$

$DID^{pl}_{+,t,\ell}$ compares the outcome evolution in groups treated for the first time in $t-\ell$ and i2n groups untreated from period 1 to t, as $DID_{+,t,\ell}$, but between periods $t-2\ell-2$ to $t-\ell-1$ instead $t-\ell-1$ and t. Thus, this estimator testing if common trends holds for $\ell+1$ periods. If those placebos are statistically insignificant, this is evidence that groups switching and not switching treatment are on common trends. Under this assumption, the DID estimator is unbiased for the effect of the first time treatment switch, ℓ periods after the groups took it [5].

5 Results

5.1 Testing the identifying assumption

As previously discussed, the identifying assumption is verified by the placebo test described above. The assumption will fail if the groups that take the internships and those that do not take them to show a different behavior before the first semester where the treatment is taken (that is, t = 0). In contrast, the assumption will be fulfilled if the two groups show a similar behavior or trends before one of them starts with the internships. In the placebo test, this is true if the groups do not have a statistically significant difference on average academic performance before starting treatment.

Figure 2 shows that there is no different behavior between the group of students who do not do internships and those who do before the first semester in which they take it, that is when t is equal to 0. This result is an application of the placebo test proposed in the previous section. The application of this test, in the specification without controls, does not reject the null hypothesis that the two groups have statistically similar changes in academic performance before the first semester in which the treatment-adopting group takes the treatment.

In addition, the similar behavior observed pre-treatment between the two groups, internship and non-internship students, is robust across the three different specifications, including College fixed effects and an interaction term capturing the fixed effect of each College across semesters. Similarly, a joint placebo test was performed for the 3 different specifications, which resulted in a p-value of more than 0.05 [6]. This result shows that all requested placebos, altogether, are equal to 0, i.e, there is no evidence of pre-treatment effect of preprofessional internships on student academic performance.

5.2 Estimation of treatment effects

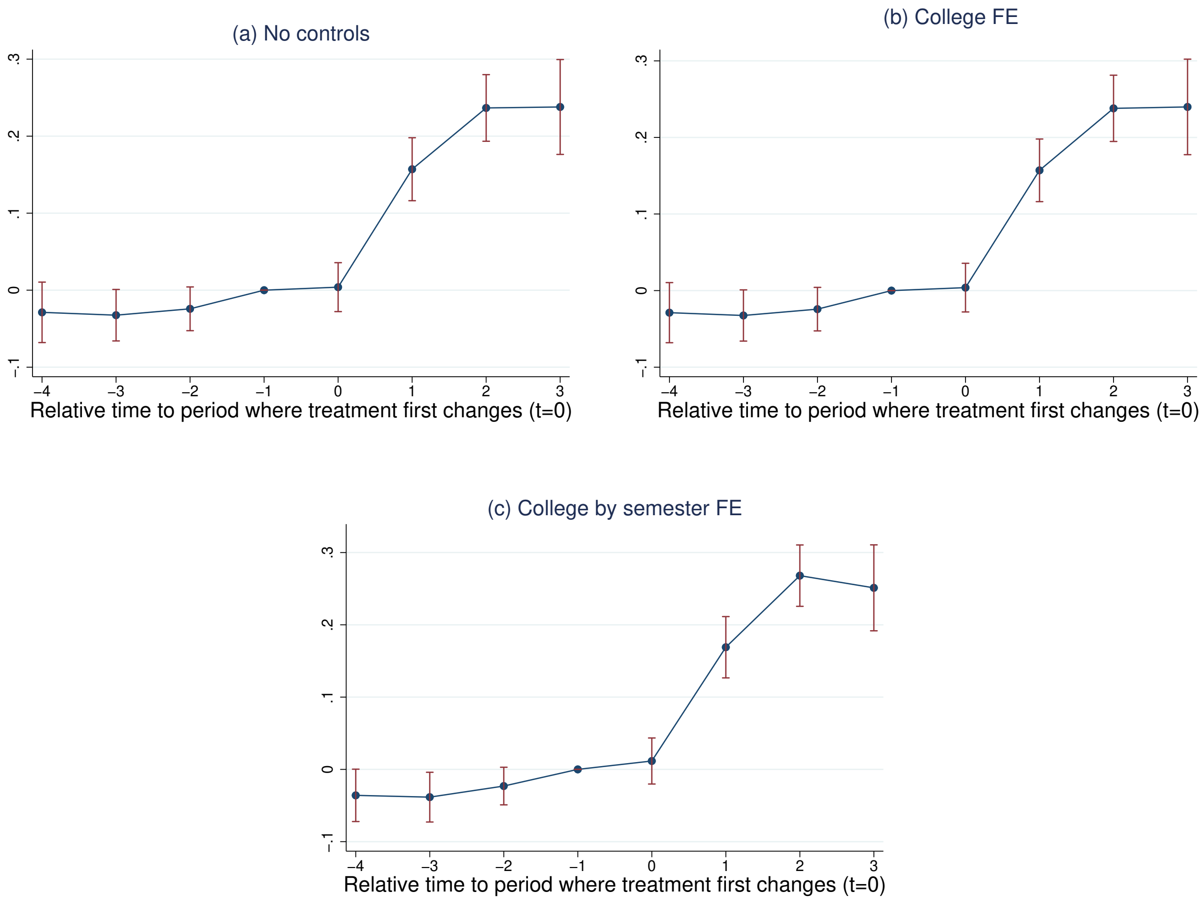
This subsection analyzes the immediate ,dynamic and aggregate effect of the internships on student academic performance. To examine the dynamic effects on students' academic performance once they take internships, I use Figure 2, however, this time I focus on the effects when t is equal or greater than 0, which indicates the effect in the semester in which the student takes the internship and its effects in the future.

The figure shows that there is a large change in students' academic performance after taking an internship for the first time. On average, there is no immediate effect of internships on students'

[5]For example, if ℓ is equal to 0, the instantaneous effect is estimated, while if ℓ is equal to 1, the effect of having received the treatment 1 period ago is estimated.

[6]The null hypothesis is that all the placebos requested are equal to 0

Figure 2: Placebo and dynamic effects of internships on academic performance



Note: Figure a is the regression result that does not include any fixed effect for students' faculties. Figure b represents the regression result that includes the college fixed effects, while Figure c includes the interaction terms between the College fixed effects and semesters.Confidence intervals are calculated at 95 percent and standard errors are clustered at the student level.

academic performance when they take them. However, a positive and significant effect is observed in their subsequent semesters. This result is observed across the 3 main specifications in Figure 2, proving the robustness of the internship effect.

In summary, Table 2 shows all the effects found, both immediate and dynamic. In addition, this table shows the aggregate average effect of the internships on students' academic performance. To test the robustness of the effects , I start with column 1, which represents the basic specification of equation 1. Nonetheless, due to the diversity of faculties in the university and the different types of internship programs in each of them, column 2 incorporates College fixed effects into the main specification, and, column 3 introduce fixed effects by faculties interacted with semesters fixed effects to allow for a component that takes into account a possible change or policy of each College that may occur in a specific semester regarding internships.

The aggregate internship effect on students' academic performance is between 0.239 and 0.266 academic points, what represent 3.4 % and 3.8% respect the students academic performance mean. Results show that the treatment effects of the internships are robust to the any fixed factor that vary by College. Furthermore, the effects of the internships are robust to the insertion of interactions between semester fixed effects and faculties.

Table 2: Dynamic and aggregate effect of professional internships on students' academic performance

	(1)	(2)	(3)	*Switchers*
Placebo 3	-0.029	-0.029	-0.036*	2726
	(0.020)	(0.020)	(0.018)	
Placebo 2	-0.032*	-0.032*	-0.038**	4345
	(0.017)	(0.017)	(0.018)	
Placebo 1	-0.024*	-0.024*	-0.023*	5360
	(0.014)	(0.014)	(0.013)	
Semester 0	0.004	0.004	0.012	5560
	(0.016)	(0.016)	(0.018)	
Semester +1	0.157***	0.157***	0.169***	4667
	(0.021)	(0.021)	(0.022)	
Semester +2	0.237***	0.238***	0.268***	3152
	(0.022)	(0.022)	(0.022)	
Semester +3	0.238***	0.240***	0.251***	2055
	(0.031)	(0.032)	(0.030)	
Agg. average effect	0.239***	0.240***	0.266***	15434
	(0.029)	(0.029)	(0.031)	
College FE	No	Yes	Yes	
College by semester FE	No	No	Yes	
Joint placebo test (p-value)	0.19	0.14	0.07	

Note: Bootstrapped standard errors clustered at the student level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

One of the goals of the professional internships is that students to apply the knowledge acquired during their studies and develop specific skills and abilities for adequate performance in their professional future and academic life. The results described above effectively show that the objective of these programs is achieved. However, these results are not the same for all students.

Using the start and end dates of the internships recorded in the administrative database, I re-estimate the variable of internships and identify, within the group that take the treatment, students who do their internships during the total semester, and those who do the internships partially, i.e., who do not use the total semester time to do them. With these two new groups identified, I re-estimate the effects of internships on academic performance using the following equation:

$$Y_{ist} = \alpha_i + \lambda_t + \sum_{\ell=-4}^{3} \beta^{\ell} Intern * Full_{it} + \sum_{\ell=-4}^{3} \gamma^{\ell} Intern * (1 - Full)_{it} + \delta_{st} + X_i'\theta + \mu_{ist} \quad (9)$$

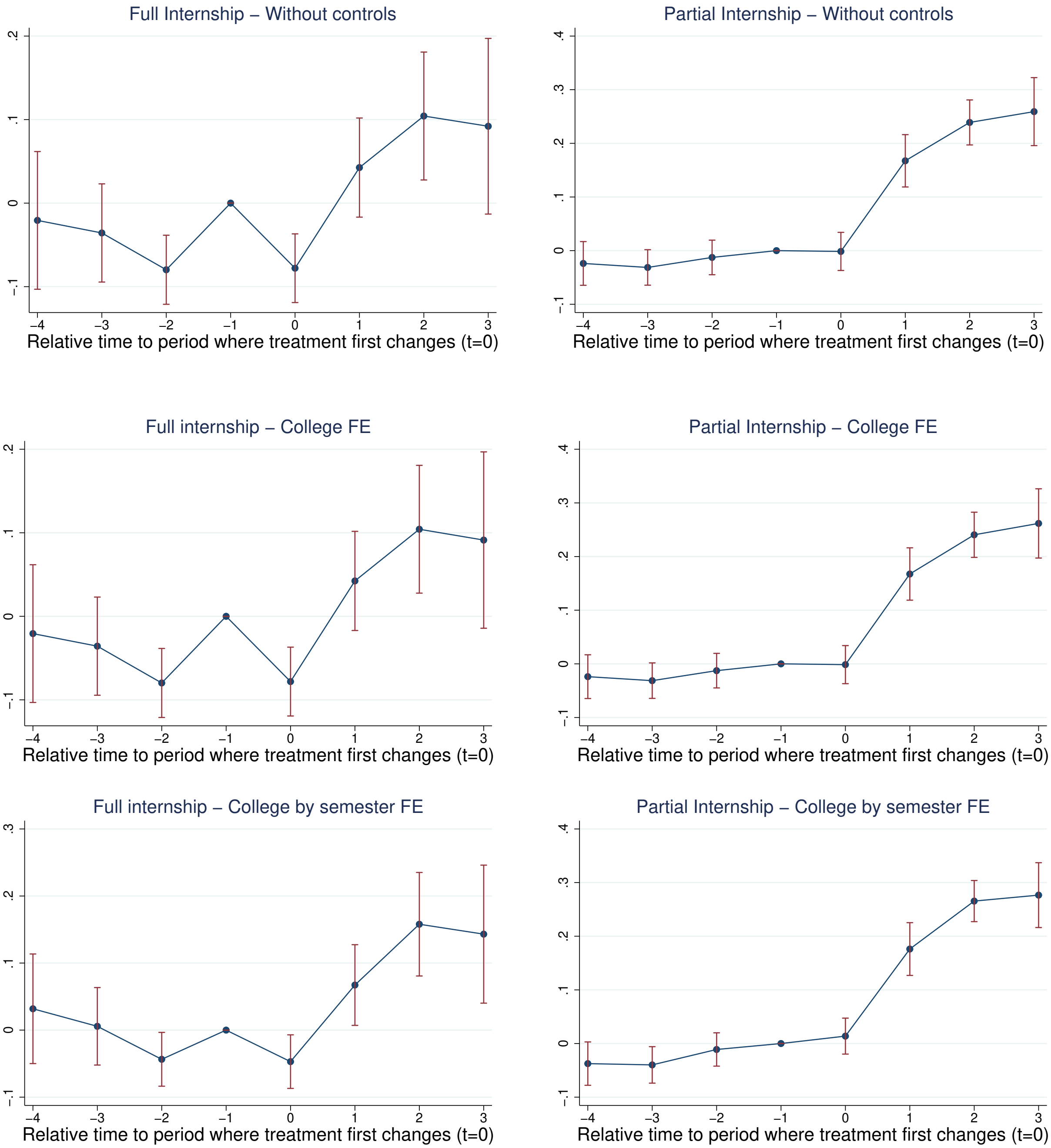
where $Full_{it}$ represents student i who took an internship and spent all the semester t time doing it. Thus, the coefficient β^{ℓ} captures the immediate and dynamic effect of taking an internship for the total semester on the student's academic performance, while the coefficient γ^{ℓ} reflects the effects on academic performance of taking the internship partially. When estimating the effect of full internships , the control group is those who completed partial internships and those who did not complete internships. When estimating the effect of partial internships, the control group is those who completed full internships and those who have not completed internships.

Figure 3 summarizes the results of the effect of full and partial internships on students' academic performance. Also, the figure shows the behavior of these two groups before treatment to test the joint placebo test. In contrast to the initial results, students who take their internships for the whole semester show an negative immediate effect of taking the internship for the first time on academic performance , i.e., they score lower in their grades when they are doing their internships for the first time, while those who take the internship partially have no immediate effect on their academic performance. On the other hand, the behavior of the two groups in the future looks similar, the effect of internships after taking the treatment for the first time is positive, but the magnitude and robustness of the effect for the two groups is different. The effect of partial internships looks like has a larger magnitude than those who do their internships for their total semester.

To test the robustness of these results, Table 3 summarizes the effects of full internships (Panel A) and partial internships (Panel B) across several specifications, furthermore, I calculate the same effects by conditioning my data to keep only students who do full or partial internships and those who do not, in order to have a single comparison group.

The results show that the aggregate average effect on academic performance is greater for those who do partial internships than for those who do internships for the entire semester. For the general estimation, the difference in the average aggregate treatment effect, in favor of partial internships, is between 0.205 and 0.239 academic points, while for the conditional estimation this difference is between 0.211 and 0.255 academic points, proving robustness in their results. In adition, the immediate effect for those who do partial internships is better, since there is no negative effect on their grades; however, for those who spend all their semester time in the internship program there is a negative effect between 0.045 and 0.078 academic points.

Figure 3: Placebo and dynamic effects of partial and full internship on academic performance



Note: The results without controls do not include any fixed effect for students' faculties. The College FE represents the regression result that includes the faculties fixed effects, while the College by semester FE results include the interaction terms between the College fixed effects and semesters fixed effects. Confidence intervals are calculated at 95 percent and standard errors are clustered at the student level.

Table 3: Effects of partial and full internship on academic performance

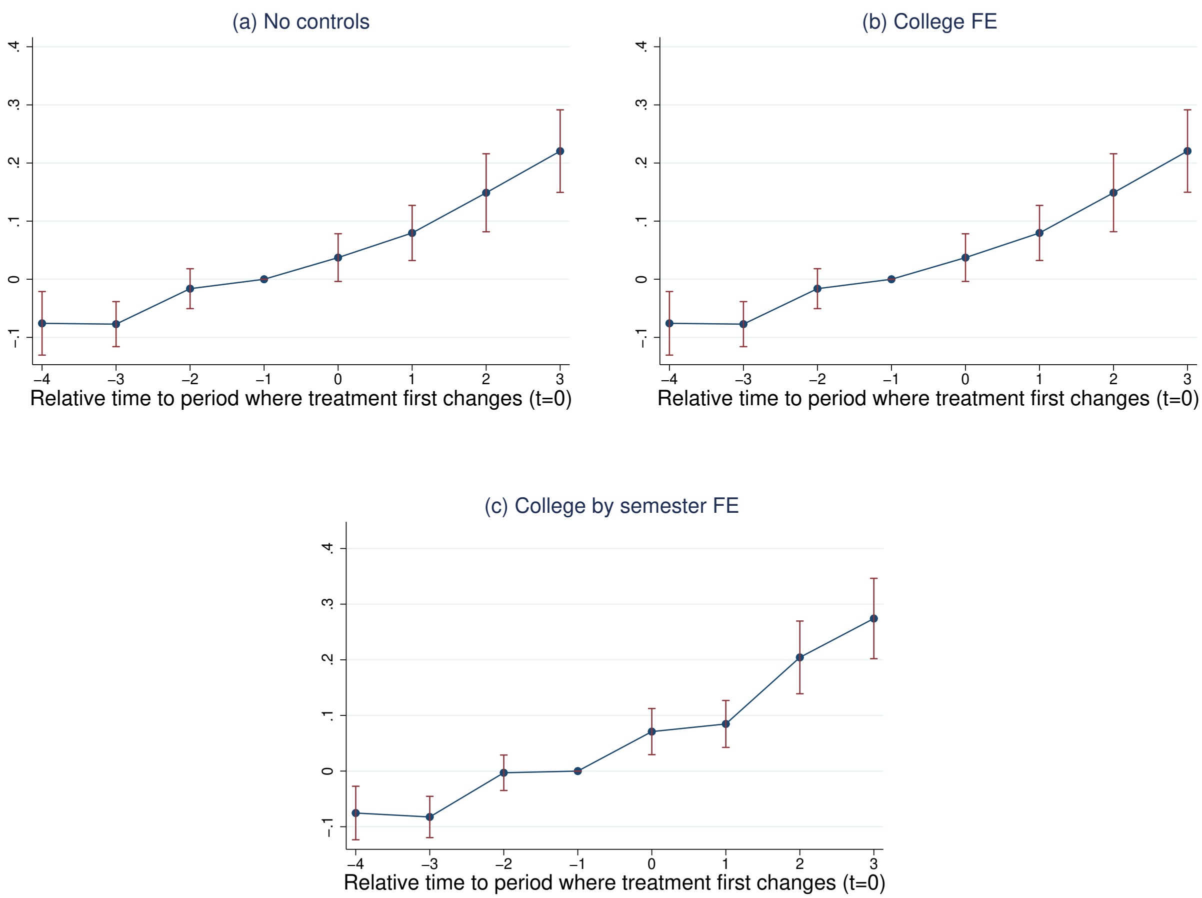
	Academic performance				Academic performance - Conditional estimation			
	(1)	(2)	(3)	*Switchers*	(4)	(5)	(6)	*Switchers*
Panel A: Full internship								
Placebo 3	-0.021	-0.021	0.032	850	-0.002	-0.002	-0.012	426
	(0.042)	(0.042)	(0.042)		(0.044)	(0.044)	(0.043)	
Placebo 2	-0.036	-0.036	0.006	1260	-0.016	-0.016	-0.014	708
	(0.030)	(0.030)	(0.029)		(0.036)	(0.036)	(0.035)	
Placebo 1	-0.078***	-0.080***	-0.044**	1602	-0.056**	-0.056**	-0.059**	1115
	(0.021)	(0.021)	(0.020)		(0.025)	(0.026)	(0.024)	
Semester 0	-0.078***	-0.078***	-0.045***	1701	-0.064**	-0.064**	-0.064**	1160
	(0.021)	(0.021)	(0.020)		(0.028)	(0.028)	(0.027)	
Semester +1	0.043	0.042	0.067 **	1442	0.052	0.051	0.053	756
	(0.030)	(0.030)	(0.031)		(0.052)	(0.052)	(0.051)	
Semester +2	0.104***	0.104***	0.158***	1077	0.168***	0.168***	0.181***	468
	(0.039)	(0.039)	(0.142)		(0.058)	(0.058)	(0.061)	
Semester +3	0.092*	0.091*	0.143***	769	0.181**	0.180**	0.181**	282
	(0.054)	(0.054)	(0.053)		(0.083)	(0.083)	(0.087)	
Aggregate average effect	0.042	0.041	0.111**	4984	0.060	0.060	0.064	2666
	(0.046)	(0.046)	(0.046)		(0.054)	(0.054)	(0.054)	
Panel B: Partial internship								
Placebo 3	-0.024	-0.024	-0.037*	2262	-0.029	-0.029	-0.036*	1821
	(0.021)	(0.021)	(0.021)		(0.027)	(0.027)	(0.027)	
Placebo 2	-0.031*	-0.031*	-0.040**	3661	-0.035*	-0.035*	-0.040**	3112
	(0.017)	(0.017)	(0.017)		(0.019)	(0.019)	(0.018)	
Placebo 1	-0.013	-0.013	-0.011	4505	-0.016	-0.016	-0.021	4235
	(0.016)	(0.016)	(0.016)		(0.016)	(0.016)	(0.015)	
Semester 0	-0.001	-0.001	0.014	4772	0.007	0.007	0.018	4491
	(0.018)	(0.018)	(0.017)		(0.014)	(0.014)	(0.013)	
Semester +1	0.167***	0.167***	0.176***	4015	0.191***	0.191***	0.208***	3326
	(0.025)	(0.025)	(0.025)		(0.022)	(0.022)	(0.022)	
Semester +2	0.239***	0.241***	0.266***	2602	0.257***	0.259***	0.301***	2058
	(0.021)	(0.039)	(0.020)		(0.027)	(0.027)	(0.029)	
Semester +3	0.259***	0.262***	0.277***	1671	0.268***	0.271***	0.330***	1235
	(0.032)	(0.033)	(0.031)		(0.047)	(0.048)	(0.049)	
Agg. Average Effect	0.281***	0.282***	0.315***	13060	0.271***	0.273***	0.319***	11110
	(0.035)	(0.035)	(0.032)		(0.029)	(0.029)	(0.031)	
College FE	No	Yes	Yes		No	Yes	Yes	
College by semester FE	No	No	Yes		No	No	Yes	

Note: Bootstrapped standard errors clustered at the student level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The estimates in columns 1, 2 and 3 are obtained by applying equation 9 described above. The results in columns 4, 5 and 6 have a condition in their estimation. To estimate the effect of full internships, I drop the group of students who take partial internships, the only control group being those who have not done the internships. The same to estimate the effect of partial internships.

In practice, the estimated effects of full and partial internships on the behavior of their academic performance may be due to their dedication and concentration on a single activity, given that students must allocate their time between hours of study or professional activities hours. For this reason, to explore this issue, I estimate the effects of take internships at times when students do not have class hours, for example, during their class break period.

As before, using the start and end dates of internships recorded in the administrative database, I identify those students who complete their internships in the class break periods, i.e., those who do not allocate any semester time to the completion of their internships. With this variable, I estimate the effect of class break internships in the semester immediately following the class break period, in future semesters and the average aggregate effect.

Figure 4: Placebo and dynamic effects of class break internships on academic performance



Note: Figure 4a is the regression result that does not include any fixed effect for students' faculties. Figure 4b represents the regression result that includes the college fixed effects, while Figure 4c includes the interaction terms between the College fixed effects and semesters.Confidence intervals are calculated at 95 percent and standard errors are clustered at the student level.

Figure 4 and Table 4 show the results of the effects of class break internships on students' immediate and dynamic academic performance. It can be clearly seen that, as in the original results, there is a positive effect on students' academic performance after they have completed their first internship. However, it is evident that internships in these periods have an immediate positive effect, causing the average aggregate effect to be greater than the aggregate effect found in Table 2. This result suggests that students should consider taking their internships during class break periods, so that, even though they take them in all the time of class break period, there is no immediate negative effect on their grades and they can take advantage of the study time during their classes.

Table 4: Dynamic and aggregate effect of class break professional internships on students' academic performance

	(1)	(2)	(3)	*Switchers*
Placebo 3	-0.076***	-0.076***	-0.075***	242
	(0.028)	(0.028)	(0.025)	
Placebo 2	-0.078***	-0.077***	-0.082***	379
	(0.020)	(0.020)	(0.019)	
Placebo 1	-0.016	-0.016	-0.003	435
	(0.018)	(0.018)	(0.018)	
Semester 0	0.037*	0.037*	0.071***	436
	(0.021)	(0.021)	(0.021)	
Semester +1	0.080***	0.080***	0.085***	381
	(0.024)	(0.024)	(0.022)	
Semester +2	0.149***	0.149***	0.204***	245
	(0.034)	(0.034)	(0.033)	
Semester +3	0.220***	0.221***	0.274***	150
	(0.036)	(0.036)	(0.037)	
Aggregate average effect	0.256***	0.256***	0.339***	1212
	(0.050)	(0.050)	(0.047)	
College FE	No	Yes	Yes	
College by semester FE	No	No	Yes	

Note: Bootstrapped standard errors clustered at the student level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

One of the reasons why students would decide to allocate all of their semester time to study and take an internship would be that they have an economic incentive to do so. For this reason, I identify those students who do paid internships and those who do them without receiving any remuneration. With these groups, I estimate the effect of doing a paid and unpaid internship on academic performance using a similar equation as before with the full and partial internships:

$$Y_{ist} = \alpha_i + \lambda_t + \sum_{\ell=-4}^{3} \beta^{\ell} Intern * Paid_{it} + \sum_{\ell=-4}^{3} \gamma^{\ell} Intern * (1 - Paid)_{it} + \delta_{st} + X_i'\theta + \mu_{ist} \tag{10}$$

where $Paid_{it}$ represents student i who took a paid internship. Thus, the coefficient β^{ℓ} captures the immediate and dynamic effect of taking an internship where the student receive a salary, while the coefficient γ^{ℓ} reflects the effects of unpaid internship on academic performance.

Figure 5 and Table 5 show the results of the paid and unpaid internships effects on academic performance. Indeed, students who take paid internships also show lower academic performance in the immediate semester in which they take them. The immediate effect of paid internships is negative and is between 0.108 and 0.118 academic points in the overall estimation. Likewise, in the conditional estimation, the immediate effect remains negative and is between 0.083 and 0.091 academic points. This is not the case for students who take unpaid internships. There is no statistically significant immediate effect of unpaid internships on academic performance. Besides, the aggregate results favor unpaid internships compared to paid students.. The difference in the average aggregate effect for unpaid interns compared to paid interns is large. The difference is between 0.392 and 0.422 academic points using the overall estimate and 0.309 and 0.342 academic points with the conditional estimation. These results may be due, as before, to the time that students dedicate to their professional internship activities, due the existence of economic remuneration increases the incentives to dedicate more hours of their time to internships than to study hours.

In addition, the same specifications were estimated taking as the outcome variable the number of credits selected by students. In general, it is clear that there is a drastic change in the number of credits selected (Figure 9). The aggregate average effect of taking an internship for the first time on the number of credits selected is between 2,058 and 2,253 fewer credits selected by those who take internships compared to those who do not (Table 7). Analyzing the results by internship duration, heterogeneous results are found. Students who take full internships have a higher average aggregate reduction in the number of credits than those who take partial internships.The most dramatic change is evident when the first internships students take are paid. The average aggregate effect of paid internships is between a reduction of 2,708 and 2,728 number of credits, while, for those students who take unpaid internships, the effect is a reduction of between 1,875 and 1,912.

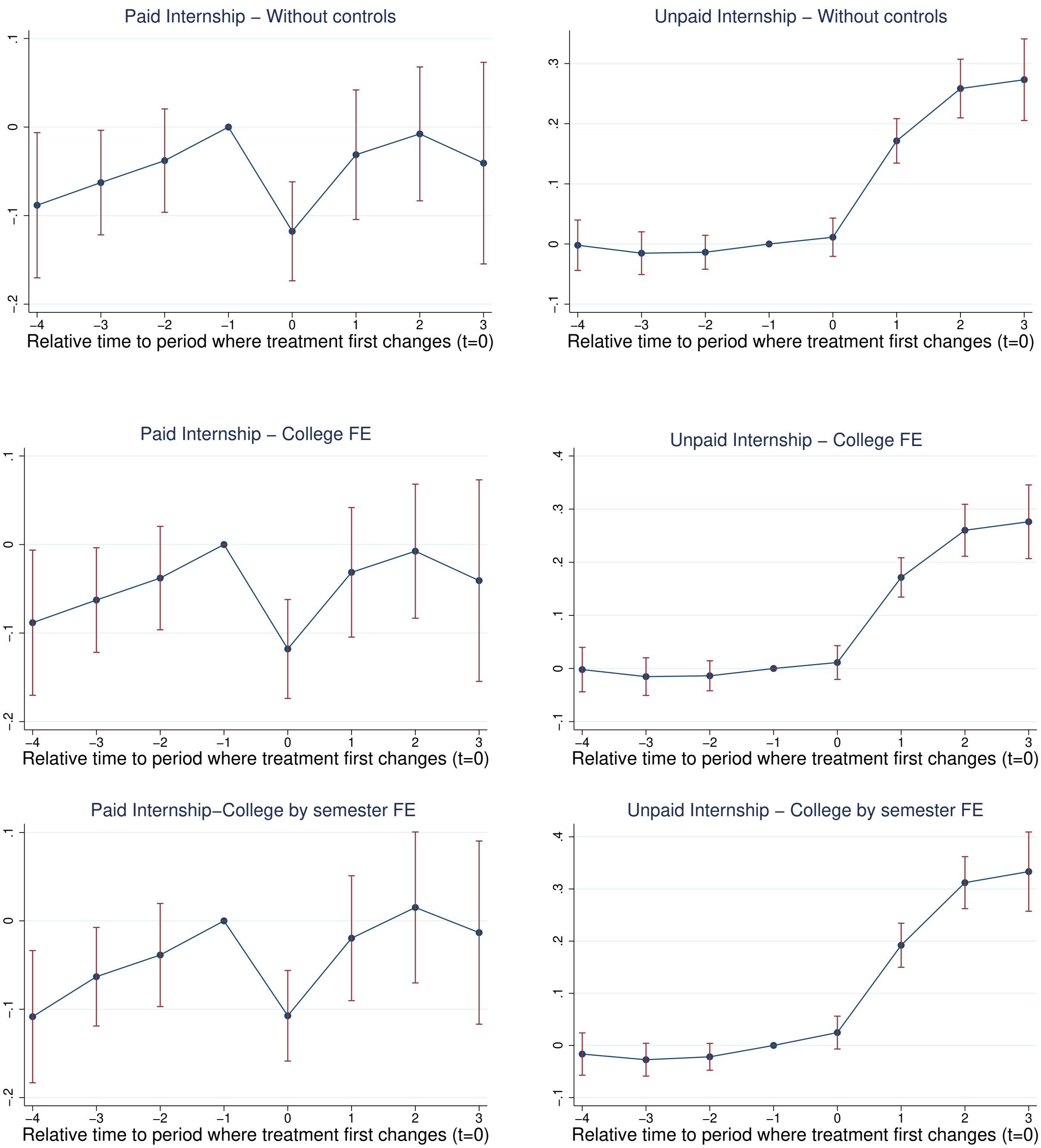
Nonetheless, class break internships also turn out to be the best alternative in terms of the number of credits selected, considering that one of the main objectives of academic institutions is to improve the terminal efficiency of their students. Although the average aggregate effect of class break internships on the number of credits selected is also negative, the reduction is between 1.074 and 1.176, suggesting that, on average, students who take class break internships take 1.03 more credits than those who take them during classes. Again, this result suggests the choice of class break periods to take these programs. Details of the results of the effects of class break internships on the number of credits can be found in the appendix section.

Table 5: Effects of paid and unpaid internships on academic performance

	GPA				GPA - Conditional estimation			
	(1)	(2)	(3)	*Switchers*	(4)	(5)	(6)	*Switchers*
Panel A: Paid internship								
Placebo 3	-0.089**	-0.089**	-0.108***	619	-0.085**	-0.085**	-0.109***	560
	(0.042)	(0.042)	(0.038)		(0.037)	(0.037)	(0.039)	
Placebo 2	-0.063**	-0.063**	-0.063**	1018	-0.070**	-0.070**	-0.068**	945
	(0.030)	(0.030)	(0.030)		(0.030)	(0.030)	(0.029)	
Placebo 1	-0.038	-0.038	-0.039	1352	-0.040	-0.040	-0.039	1270
	(0.030)	(0.030)	(0.030)		(0.024)	(0.024)	(0.024)	
Semester 0	-0.118***	-0.118***	-0.108***	1372	-0.091**	-0.091**	-0.083***	1312
	(0.029)	(0.029)	(0.026)		(0.026)	(0.026)	(0.028)	
Semester +1	-0.031	-0.031	-0.020	1066	0.021	0.021	0.026	998
	(0.037)	(0.037)	(0.036)		(0.041)	(0.041)	(0.042)	
Semester +2	-0.008	-0.008	0.015	693	0.068	0.068	0.082	619
	(0.039)	(0.039)	(0.044)		(0.055)	(0.055)	(0.052)	
Semester +3	-0.041	-0.041	-0.013	460	0.067	0.067	0.095	405
	(0.058)	(0.058)	(0.053)		(0.095)	(0.095)	(0.101)	
Aggregate average effect	-0.111***	-0.111***	-0.083***	3591	-0.016	-0.016	0.002	3334
	(0.043)	(0.043)	(0.040)		(0.052)	(0.052)	(0.056)	
Panel B: Unpaid internship								
Placebo 3	-0.002	-0.002	-0.017	2173	-0.004	-0.004	-0.017	2104
	(0.021)	(0.021)	(0.021)		(0.023)	(0.023)	(0.022)	
Placebo 2	-0.015	-0.015	-0.027*	3463	-0.018	-0.018	-0.029**	3377
	(0.018)	(0.018)	(0.016)		(0.016)	(0.016)	(0.014)	
Placebo 1	-0.014	-0.014	-0.022*	4177	-0.017	-0.017	-0.025	4121
	(0.014)	(0.014)	(0.013)		(0.013)	(0.013)	(0.012)	
Semester 0	0.011	0.011	0.025	4357	0.012	0.012	0.025	4318
	(0.016)	(0.016)	(0.016)		(0.012)	(0.012)	(0.012)	
Semester +1	0.171***	0.171***	0.192***	3740	0.180***	0.180***	0.198***	3660
	(0.019)	(0.019)	(0.022)		(0.016)	(0.016)	(0.019)	
Semester +2	0.258***	0.260***	0.312***	2544	0.279***	0.281***	0.331***	2459.00
	(0.025)	(0.025)	(0.025)		(0.024)	(0.024)	(0.027)	
Semester +3	0.273***	0.276***	0.333***	1647	0.291***	0.293***	0.341***	1574
	(0.035)	(0.035)	(0.039)		(0.031)	(0.031)	(0.034)	
Aggregate average effect	0.281***	0.282***	0.339***	12288	0.293***	0.294***	0.344***	12011
	(0.031)	(0.031)	(0.036)		(0.023)	(0.023)	(0.026)	
College FE	No	Yes	Yes		No	Yes	Yes	
College by semester FE	No	No	Yes		No	No	Yes	

Note: Bootstrapped standard errors clustered at the student level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The estimates in columns 1, 2 and 3 are obtained by applying equation 10 described above. The results in columns 4, 5 and 6 have a condition in their estimation.

Figure 5: Placebo and dynamic effects of paid and unpaid internships on academic performance



Note: The results without controls do not include any fixed effect for students' faculties. The College FE represents the regression result that includes the faculties fixed effects, while the College by semester FE results include the interaction terms between the College fixed effects and semesters fixed effects. Confidence intervals are calculated at 95 percent and standard errors are clustered at the student level.

6 Conclusions

This paper studies the immediate and dynamic effect of internships on the academic performance and number of selected credits at ESPOL students in Ecuador. I identify this effect using a new difference-in-differences estimator that, unlike the traditional estimator (TWFE), is robust to heterogeneous and dynamic effects. To test the main identification assumption, a placebo test is used to determine whether there was any difference on average academic outcomes between students who took internships and those who did not, before the first time they took them.

The results indicate that internships significantly increase students' academic performance after taking them. However, I also find that there is a heterogeneous effect among those who take internships. Programs that are taken for the entire time of the semester have an immediate negative effect on students' academic performance, not so with those that are taken partially, which have a larger positive aggregate effect on students' academic performance. In addition, taking internships during vacation periods, where students do not have to allocate their time to taking classes, has an immediate positive effect on their grades. In fact, on average, vacation internships increase academic performance by a larger magnitude compared to those taken during a regular semester of classes. I also find evidence that the effect of unpaid internships is greater than paid internships. In fact, paid internships have an immediate negative effect on students' academic performance.

Additional results show that on average, internships also have a negative effect on the number of credits students select after taking them. However, as with academic performance, taking these programs on a partial or unpaid way has less of a negative effect on credits selection. Finally, it was also shown that vacation internships turn out to be the best alternative for not greatly decreasing the number of credits selected.

These results are informative for decision makers regarding educational policies in higher education systems. One recommendation that emerges from the results is that the decision about the ideal timing of internships has an important implication on students' academic performance and terminal efficiency. A direct policy implication for higher education authorities at the international level, already taken by universities in Ecuador, is to implement schemes where vacation internships can be taken, or to limit the possibility of being able to take this type of program in schemes where the incentives to dedicate more time to them are greater than those of allocating more time to study hours.

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7 Appendix

Table 6: Effect of internships on academic performance. Two-way fixed effect estimation.

	(1)	(2)	(3)	(4)	(5)
	POLS	POLS	FE	TWFE	TWFE
Internship aggregate effect	0.707***	0.652***	0.135***	0.009	0.009
	(0.014)	(0.014)	(0.01)	(0.011)	(0.011)
Obs.	148321	147614	147614	147614	147614
Controls	No	Yes	Yes	Yes	Yes
Students FE	No	No	Yes	Yes	Yes
Time FE	No	No	No	Yes	Yes

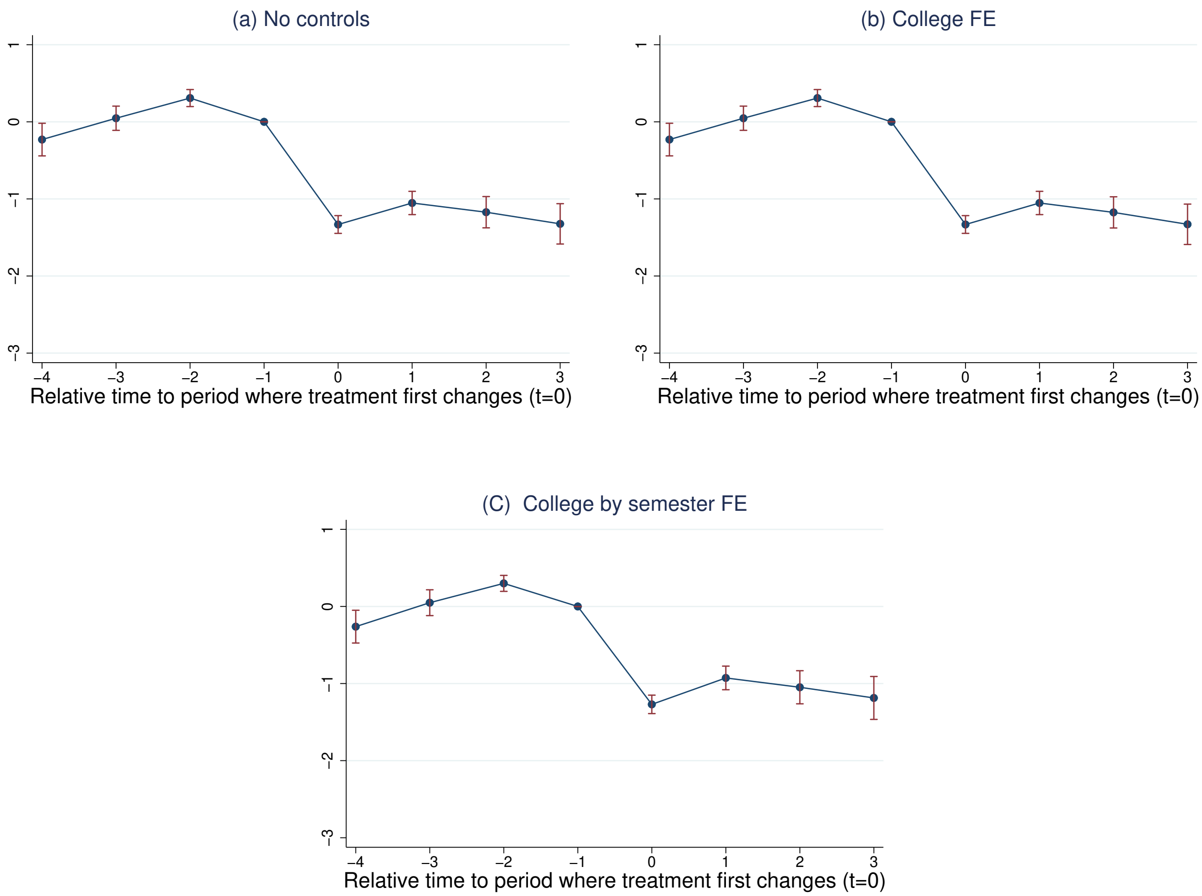
Note: Standard errors clustered at the student level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Dynamic and aggregate effect of internships on the number of credits selected.

	(1)	(2)	(3)	*Switchers*
Semester 0	-1.332***	-1.332***	-1.270***	5560
	(0.059)	(0.059)	(0.061)	
Semester +1	-1.053***	-1.053***	-0.927***	4667
	(0.077)	(0.077)	(0.078)	
Semester +2	-1.173***	-1.175***	-1.048***	3152
	(0.103)	(0.103)	(0.110)	
Semester +3	-1.324***	-1.329***	-1.187***	2055
	(0.133)	(0.134)	(0.142)	
Aggregate average effect	-2.251***	-2.253***	-2.058***	15434
	(0.123)	(0.123)	(0.125)	
Faculty FE	No	Yes	Yes	
Faculty by semester FE	No	No	Yes	

Note: Bootstrapped standard errors clustered at the student level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 6: Placebo and dynamic effects of internships on number of credits selected



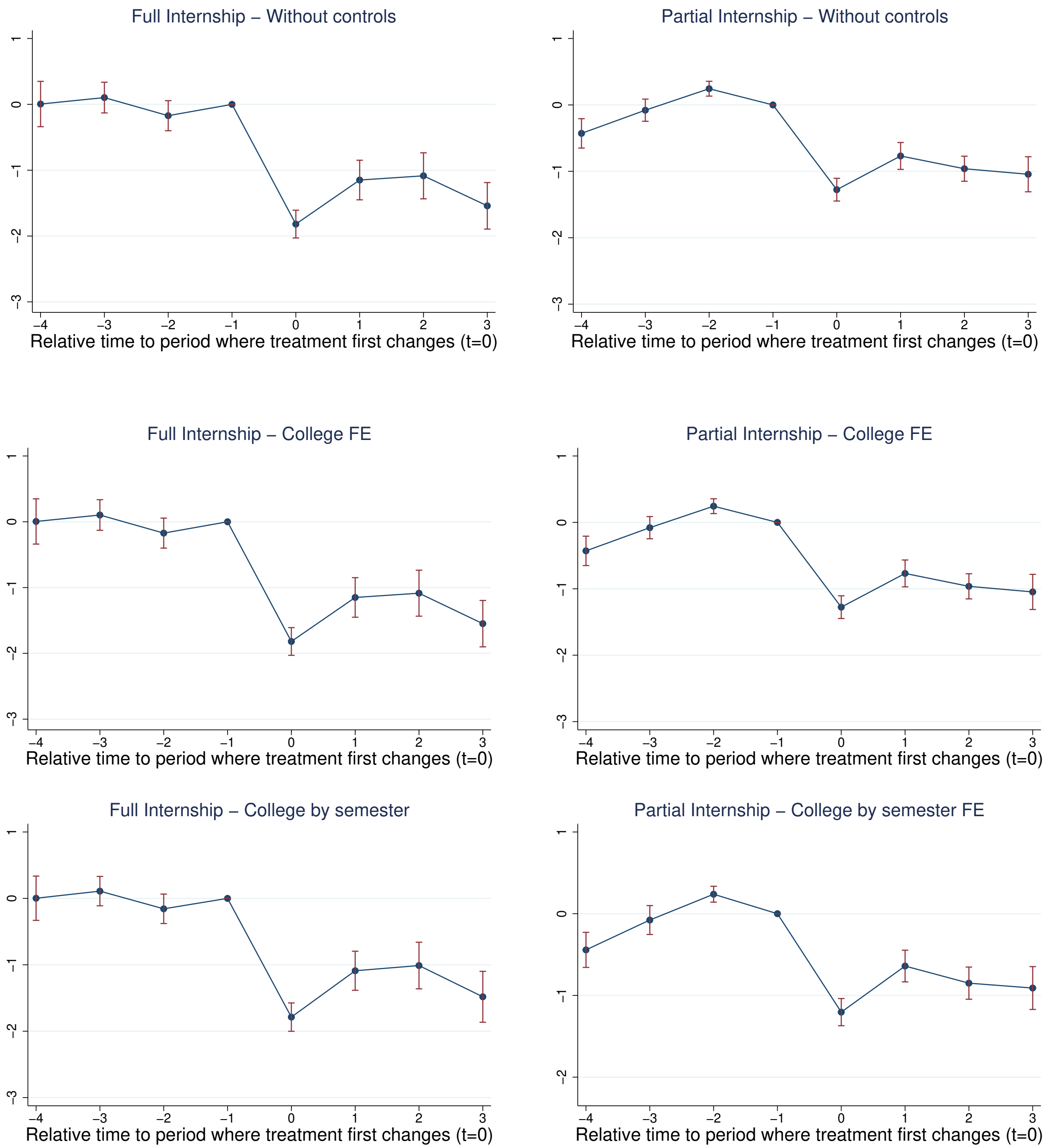
Note: Figure a is the regression result that does not include any fixed effect for students' faculties. Figure b represents the regression result that includes the college fixed effects, while Figure c includes the interaction terms between the faculty fixed effects and semesters.Confidence intervals are calculated at 95 percent and standard errors are clustered at the student level.

Table 8: Effects of partial and full internship on number of credits selected

	Number of credits				Number of credits - Conditional Estimation			
	(1)	(2)	(3)	Switchers	(4)	(5)	(6)	Switchers
Panel A: Full internship								
Semester 0	-1.819***	-1.819***	-1.788***	1701	-1.897***	-1.898***	-1.871***	1160
	(0.108)	(0.108)	(0.109)		(0.146)	(0.146)	(0.146)	
Semester +1	-1.150***	-1.150***	-1.109***	1442	-1.226***	-1.226***	-1.189***	756
	(0.153)	(0.153)	(0.150)		(0.166)	(0.166)	(0.173)	
Semester +2	-1.085***	-1.086***	-1.011***	1077	-1.198***	-1.198***	-1.138***	468
	(0.178)	(0.178)	(0.179)		(0.219)	(0.219)	(0.233)	
Semester +3	-1.542	-1.549	-1.482	769	-1.819	-1.836	-1.916	282
	(0.180)	(0.180)	(0.196)		(0.309)	(0.306)	(0.314)	
Aggregate average effect	-2.667***	-2.670***	-2.568***	4989	-2.669***	-2.672***	-2.632***	2666
	(0.187)	(0.188)	(0.183)		(0.194)	(0.193)	(0.204)	
Panel B: Partial internship								
Semester 0	-1.276***	-1.276***	-1.204***	4772	-1.208***	-1.208***	-1.137***	4491
	(0.087)	(0.087)	(0.085)		(0.073)	(0.073)	(0.071)	
Semester +1	-0.769***	-0.769***	-0.640***	4015	-0.954***	-0.953***	-0.820***	3326
	(0.103)	(0.103)	(0.099)		(0.099)	(0.099)	(0.099)	
Semester +2	-0.961***	-0.963***	-0.850***	2602	-1.088***	-1.091***	-0.970***	2058
	(0.096)	(0.097)	(0.179)		(0.139)	(0.139)	(0.141)	
Semester +3	-1.044***	-1.047***	-0.910***	1671	-1.380***	-1.386***	-1.230***	1235
	(0.135)	(0.135)	(0.134)		(0.188)	(0.189)	(0.192)	
Aggregate average effect	-2.193***	-2.195***	-1.969***	13060	-2.225***	-2.227***	-2.013***	11110
	(0.149)	(0.151)	(0.143)		(0.163)	(0.162)	(0.163)	
Faculty FE	No	Yes	Yes		No	Yes	Yes	
Faculty by semester FE	No	No	Yes		No	No	Yes	

Note: Bootstrapped standard errors clustered at the student level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The estimates in columns 1, 2 and 3 are obtained by applying equation 9 described above. The results in columns 4, 5 and 6 have a condition in their estimation. To estimate the effect of full internships, I drop the group of students who take partial internships, the only control group being those who have not done the internships. The same to estimate the effect of partial internships.

Figure 7: Placebo and dynamic effects of full and partial internships on number of credits selected



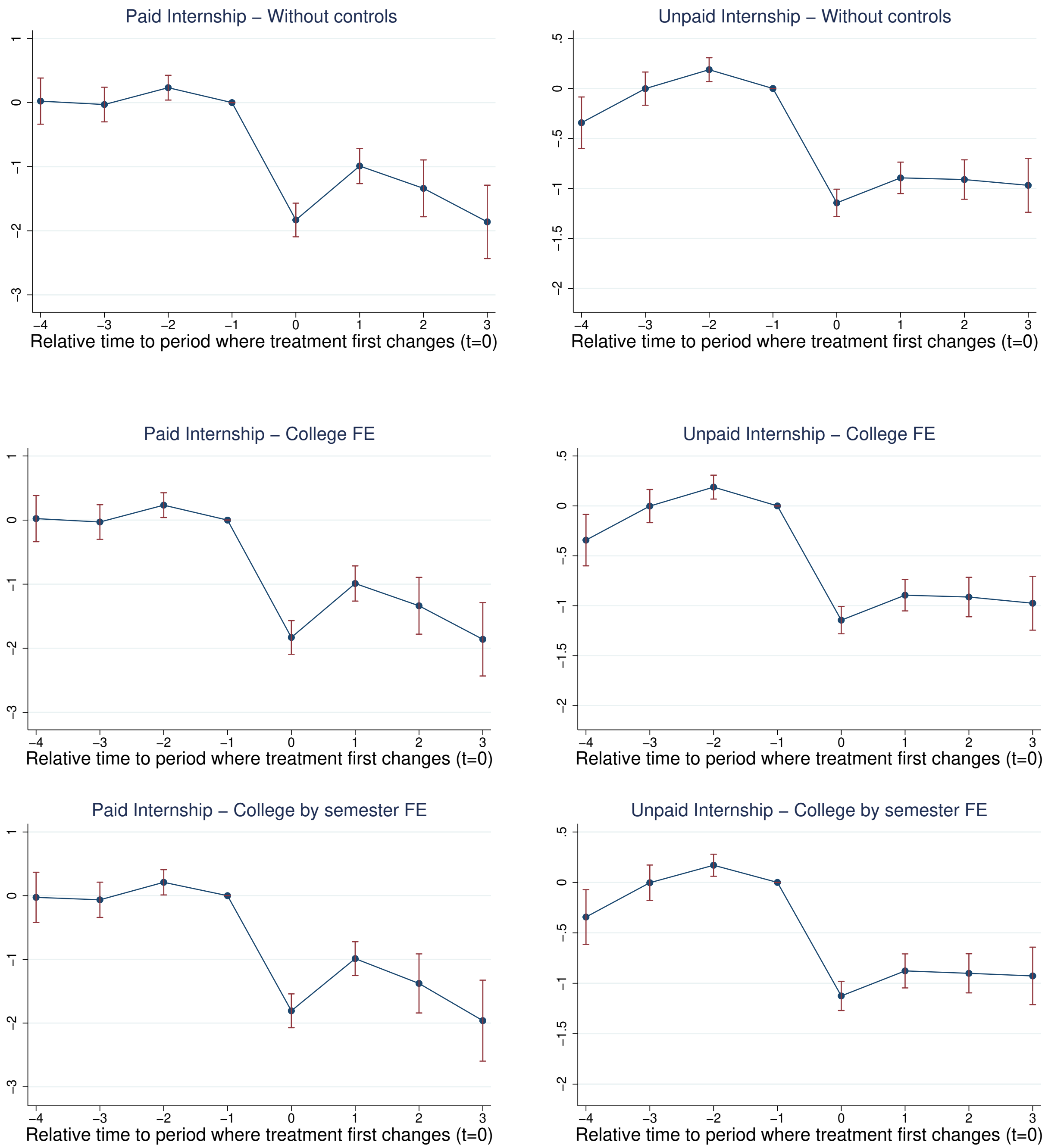
Note: The results without controls do not include any fixed effect for students' faculties. The faculty FE represents the regression result that includes the faculties fixed effects, while the faculty by semester FE results include the interaction terms between the faculty fixed effects and semesters fixed effects. Confidence intervals are calculated at 95 percent and standard errors are clustered at the student level.

Table 9: Effects of paid and unpaid internships on number of credits selected

	Number of credits				Number of credits - Conditional estimation			
	(1)	(2)	(3)	Switchers	(4)	(5)	(6)	Switchers
Panel A: Paid internship								
Semester 0	-1.831***	-1.832***	-1.807***	1372	-1.961***	-1.961***	-1.950***	1312
	(0.134)	(0.134)	(0.135)		(0.128)	(0.128)	(0.129)	
Semester +1	-0.989***	-0.990***	-0.988***	1066	-1.238***	-1.238***	-1.263***	998
	(0.140)	(0.140)	(0.135)		(0.151)	(0.151)	(0.154)	
Semester +2	-1.338***	-1.337***	-1.378***	693	-1.727***	-1.727***	-1.808***	619
	(0.226)	(0.226)	(0.236)		(0.179)	(0.179)	(0.176)	
Semester +3	-1.861***	-1.861***	-1.962***	460	-2.260***	-2.260***	-2.473***	405
	(0.292)	(0.292)	(0.324)		(0.236)	(0.236)	(0.244)	
Aggregate average effect	-2.708***	-2.708***	-2.728***	3591	-3.050***	-3.050***	-3.128***	3334
	(0.223)	(0.223)	(0.225)		(0.176)	(0.176)	(0.177)	
Panel B: Unpaid internship								
Semester 0	-1.144***	-1.144***	-1.126***	4357	-1.168***	-1.168***	-1.096***	4318
	(0.070)	(0.070)	(0.074)		(0.089)	(0.089)	(0.087)	
Semester +1	-0.894***	-0.894***	-0.877***	3740	-0.992***	-0.991***	-0.837***	3660
	(0.080)	(0.080)	(0.086)		(0.093)	(0.093)	(0.095)	
Semester +2	-0.911***	-0.912***	-0.901***	2544	-1.012***	-1.014***	-0.854***	2459
	(0.101)	(0.101)	(0.099)		(0.121)	(0.121)	(0.123)	
Semester +3	-0.969***	-0.975***	-0.927***	1647	-1.089***	-1.096***	-0.905***	1574
	(0.138)	(0.138)	(0.145)		(0.128)	(0.128)	(0.130)	
Aggregate average effect	-1.912***	-1.914***	-1.875***	12288	-2.029***	-2.032***	-1.785***	12011
	(0.149)	(0.126)	(0.132)		(0.146)	(0.147)	(0.150)	
Faculty FE	No	Yes	Yes		No	Yes	Yes	
Faculty by semester FE	No	No	Yes		No	No	Yes	

Note: Bootstrapped standard errors clustered at the student level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The estimates in columns 1, 2 and 3 are obtained by applying equation 10 described above. The results in columns 4, 5 and 6 have a condition in their estimation.

Figure 8: Placebo and dynamic effects of paid and unpaid internships on number of credits selected



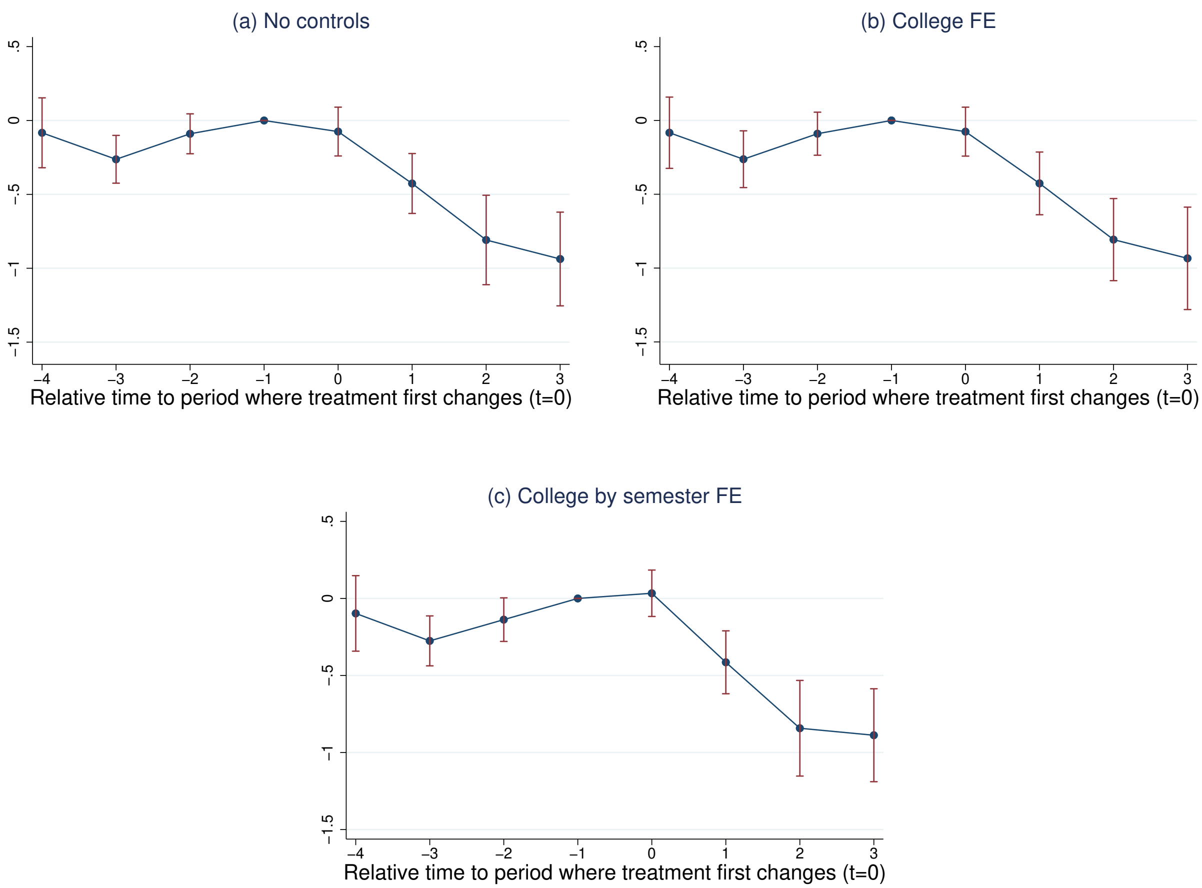
Note: The results without controls do not include any fixed effect for students' faculties. The faculty FE represents the regression result that includes the faculties fixed effects, while the faculty by semester FE results include the interaction terms between the faculty fixed effects and semesters fixed effects. Confidence intervals are calculated at 95 percent and standard errors are clustered at the student level.

Table 10: Dynamic and aggregate effect of vacation professional internships on number of credits selected

	(1)	(2)	(3)	*Switchers*
Semester 0	-0.075	-0.076	-0.034	436
	(0.084)	(0.085)	(0.077)	
Semester +1	-0.426***	-0.426***	-0.414***	381
	(0.103)	(0.108)	(0.104)	
Semester +2	-0.809***	-0.807***	-0.843***	245
	(0.154)	(0.142)	(0.158)	
Semester +3	-0.937***	-0.934***	-0.888***	150
	(0.162)	(0.177)	(0.154)	
Aggregate average effect	-1.176***	-1.175***	-1.074***	1212
	(0.209)	(0.210)	(0.202)	
Faculty FE	No	Yes	Yes	
Faculty by semester FE	No	No	Yes	

Note: Bootstrapped standard errors clustered at the student level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The estimates in columns 1, 2 and 3 are obtained by applying equation 10 described above. The results in columns 4, 5 and 6 have a condition in their estimation.

Figure 9: Placebo and dynamic effects of vacation internships on number of credits selected



Note: Figure a is the regression result that does not include any fixed effect for students' faculties. Figure b represents the regression result that includes the college fixed effects, while Figure c includes the interaction terms between the faculty fixed effects and semesters.Confidence intervals are calculated at 95 percent and standard errors are clustered at the student level.