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International student mobility and academic performance: Does timing matter?

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Abstract: In this study, we examine the impact of exchange programs' timing on students' academic performance, focusing on the moment in which students travel and the length of the period spent abroad. To provide causal evidence, we exploit unique data of more than 10,000 students from a well-known and internationalized Brazilian university from 2010 to 2020. By combing Propensity Score Matching with Difference in Differences techniques, we find that international mobility impacts groups of students differently. Students who travel closer to the end of their undergraduate courses benefit the most from the mobility experience (an increase of 0.06 points on final standardized grades), while negative effects (-0.05 points) are found for those who travel at the beginning of their university program. Our results also show that, while student mobility impacts positively and significantly students who participate in programs lasting from one semester to one year (0.08 points), negative effects are associated with shorter periods abroad (-0.1 points).

Keywords: Tertiary education, international student mobility, academic performance, grades, student achievement, propensity score matching, difference in differences

JEL Classification: I23, I26, J24

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1. Introduction

International student mobility is defined as any academic mobility outside one's local country within a student's program of study in postsecondary education (Junor and Usher, 2008). It is one of the components of transnational higher education with the most significant socioeconomic, cultural, and political implications (Guruz, 2008).

Although government support for student mobility programs is not a recent phenomenon, incentives to mobility have expanded in recent years in terms of resources involved and territories covered (Engberg et al., 2014; Guruz, 2008). From 2011 to 2018, there was a worldwide increase of 40% of student mobility at the tertiary level, going from 4 million students abroad in 2011 to an estimated 5.6 million in 2018 (UNESCO, 2021). This growth has been recorded across all regions globally, with North America and Western Europe as the favorite destinations welcoming almost half of all mobility students yearly.

It is already well established in the literature that international mobility experiences benefit students. For instance, it has been shown that going abroad boost student's soft skills (Brandenburg et al., 2016; Meya and Suntheim, 2014), reputation (Engberg et al., 2014), career prospects (Di Pietro, 2013; Parey and Waldinger, 2011), acquisition of new skills (Sorrenti, 2017; Wang et al., 2019), and student performance (Contu et al., 2020; Gonzalez-Baixauli et al., 2018; Meya and Suntheim, 2014). However, despite the amount of work on the general impacts, little attention has been dedicated to exploring heterogeneity across mobility programs, especially in terms of program design. Our work focuses on one of the dimensions differentiating international mobility programs, the temporal one.

Students can experience mobility in different moments of their academic career and stay abroad for short or more extended periods. We ask, (i) does the impact of student mobility on student performance vary across students traveling in different periods of their undergraduate program? i.e., is there a best moment to participate in student mobility?; (ii) does the impact of student mobility on student performance vary across programs with different durations? i.e., is there a best duration of a student mobility experience?

To answer those questions, we use unique data on more than ten thousand undergraduate students who graduated in the period 2010-2020 from one of the most internationalized Brazilian universities, the University of Campinas. The country choice is because, so far, most studies have focused on the impact of exchange programs using samples of European students, mainly from the Erasmus program (Brandenburg et al., 2016; Contu et al., 2020; Czarnitzki et al., 2021; Di Pietro, 2013; Gonzalez-Baixauli et al., 2018; Meya and Suntheim, 2014; Parey and Waldinger, 2011; Sorrenti, 2017; Wang et al., 2019). To the best of our knowledge, there is no study evaluating the impact of student mobility on academic performance in any Latin American country. Still, data reveal that Latin America and the Caribbean registered an increase of 40% in the number of tertiary students studying abroad from 2011 to 2018, behind only the Arab States (72%) and the Asia and Pacific region (51%) (UNESCO, 2021). Studying the impacts of student mobility in developing countries is extremely important, especially given the role of education in the development of those countries (Szirmai, 2015).

Brazil also constitutes a very suitable research context due to the process that the country has been experiencing recently. After a period of growth of the mobility phenomena, Brazil is experiencing a trend shift. Between 2000 and 2017, the population of Brazilian students studying abroad increased more than 200%, going from 18.5 to 58.9 thousand students (UNESCO, 2021). The Science without Borders initiative, sponsored by the federal government between 2011 and 2015, granted more than 90 thousand international mobility scholarships, of which 79% were for undergraduate students (Brasil, 2016). Moreover, positive spillovers generated by the initiative, the so-called "Science without Borders effect," boosted the number of scholarships even in areas not covered by the program (Granja and Carneiro, 2020; Manços, 2017).

More recently, the growing trend slowed down. The change of the Brazilian federal administration and the economic and political crisis experienced by the country has resulted in severe budget cuts in the higher education system and the financial resources dedicated to international student mobility programs (Andrade, 2019; De Negri, 2021). According to a recent report from the Institute for Applied Economic Research, a national public institution supporting Brazilian federal government public policies, federal investments fell about 37% between 2013 and 2020 (De Negri, 2021). The Ministry of Education suffered the most critical budget cut, and it is expected that this cut will directly impact the training of Brazilian researchers, both in Brazil and abroad (De Negri, 2021). Thus, it is crucial to investigate the impact of mobility programs to understand the consequences (if any) of such education budget cuts on students' future.

By applying a combination of Propensity Score Matching and Difference in Differences, we explore the causal relationship between a mobility experience and students' academic performances and find that international mobility impacted groups of students differently. For example, students who travel closer to the end of their undergraduate courses benefit the most from the mobility experience (with an increase of 0.06 points in their standardized final grades with respect to students who do not travel), while we find negative effects (-0.05 points) for those who travel at the beginning of their university program. Our results also show that, while student mobility impacts positively and significantly students who participate in programs lasting from one semester to one year (0.08 points), negative effects are associated with shorter periods abroad (-0.1 points). While there seem to be no differences between students coming from different economic and demographic settings, we find differences between students by the destination country.

This study offers empirical evidence on when and for how long students should go abroad, providing insights to policymakers engaged in maximizing the effects of mobility programs. This kind of analysis is of utmost importance, given the heterogeneity of mobility programs in the country and the varied potential effects depending on the type of mobility experience. Moreover, temporal parameters (time and duration of mobility) are variables that funding agencies and governments can adjust when designing or updating their programs.

This paper is structured as follows. First, it reviews previous studies about the impact of an exchange program on students, focusing on the effects on academic performance. Second, it details the data and the methodology chosen for the analysis. Third, the paper presents and discusses the main results of the analysis. Last, the conclusions are presented.

2. International student mobility and students' outcomes

An extensive literature has discussed the impact of international student mobility. In reviewing the literature, we group those studies along five outcome dimensions: soft skills, reputation, career prospects, acquisition of new skills, and student academic performance.

Looking at the impact of international student mobility on soft skills, Meya and Suntheim (2014) review the literature on the field and list multiple benefits of studying abroad, namely: i) positive impact on the development of students' personalities and cross-cultural skills; ii) transformation of these students into more independent, approachable and agreeable people; and iii) increased acceptance of new cultures and new ways of working. On the same line, a study about the impact of the Erasmus program on students' personalities, skills, and careers by Brandenburg et al. (2016) found that an international mobility experience generated positive changes to their personalities, influencing characteristics considered valuable to employers.[5] According to the authors, "the average change achieved in six months through the Erasmus program can be considered equivalent to a personality change that would normally happen over four years of life without Erasmus experience" (Brandenburg et al., 2016, p. 16).

Studying abroad also has a reputation effect on students. For instance, Engberg et al. (2014) pointed out that receiving the scholarship itself is already an advantage. They argued that the award is usually seen as a proxy for academic excellence, which guarantees advantages in the labor market for those who obtained

[5] Brandenburg et al. (2016) used an approach called memo©, that measured the level of six selected personality traits of students: "Tolerance of Ambiguity", "Curiosity", "Confidence", "Serenity", "Decisiveness" and "Vigour" (problem-solving skills) before and after mobility.

it. In addition, receiving high-quality training abroad and developing relationship networks could generate positive impacts on scholarship holders. The authors argue that having contact with another language and culture and expanding the beneficiaries' worldview could also be translated into personal and professional advantages.

Other studies also showed that studying abroad has several benefits in terms of career prospects. For example, Di Pietro (2013) investigated how participation in study abroad programs during university impacted subsequent employment likelihood. By drawing on a sample of Italian graduates, the author found that the probability of being employed three years after graduation increased by about 22.9 percentage points due to studying abroad. The effect was mainly driven by students from disadvantaged backgrounds (i.e., those with one or both parents with lower or upper secondary education).

Another example is the work from Parey and Waldinger (2011), which investigated the effect of studying abroad on international labor market mobility later in life for university graduates. Using a sample of five cross-sections of German students, they found that studying abroad increased the probability of working in a foreign country by about 15 percentage points. They also found that the most disadvantaged students (those who were credit constrained and had less educated parents) had the highest returns from studying abroad, showing the importance of focusing on those students to increase the return from exchange programs.

One way that studying abroad can impact employability is through the acquisition of new skills, especially language skills. Sorrenti (2017) used a sample of Italian graduates from 2007 to 2010 and found that studying abroad was essential for foreign language acquisition. However, the author found a substantial heterogeneity across languages since higher effects happened for languages close to students' native tongue, which are usually less rewarded by the labor market in terms of wage premium. Similarly, Wang et al. (2019) evaluated the benefits of a yearlong study abroad program on developing linguistic and multicultural skills measured by their academic results (overall and on languages) before and after international mobility. They used a sample of students at a British university from 2008 to 2014 and found statistically positive effects of studying abroad on academic learning.

Another branch of researchers focused on investigating the effects of participating in an international study program on students' academic performance. Meya and Suntheim (2014) investigated how studying abroad affects success at university, focusing on students from a German university between 2006 and 2011. They found that a brief study-related visit abroad significantly increased the final university grade. This increase, however, was mainly driven by the transferring of grades. They also showed that studying abroad reduced the probability of finishing university within the standard period, suggesting that higher grades came at a cost. Another example is Contu et al. (2020), which investigated if exchange programs had a positive impact on the graduation bonus of students, with a focus on those from the Erasmus program enrolled at an Italian university from 2015 to 2017. They found that the effect of international mobility on the graduation bonus was context-specific and depended on the faculty and the type of degree.

The majority of existing studies have found that students benefit from mobility programs. However, there is no full convergence of results. For instance, Gonzalez-Baixauli et al. (2018) analyzed a dataset of students from a Spanish university from 2001 to 2013 and found that, even though student mobility positively affected students' grades, the impact was not homogeneous across mobility programs or geographical areas. They also found that the increase in grades partially vanished upon returning to their home university after the mobility period. On the other hand, Czarnitzki et al. (2021) focused on a sample of Belgian students from 2006 to 2010 and found that, on average, exchange students had a decrease of 7 percent in their final grade compared to non-mobile students. That effect was heterogeneous in terms of the field of study, type of exchange, and host institution. The authors stated that the negative effect could be due to a possible mismatch between the courses taken abroad and the home university curricula, leading to exchange students not learning the required content for upcoming courses, and reducing their grades.

*

Our study adds to the work by Contu et al. (2020), Czarnitzki et al. (2021), Gonzalez-Baixauli et al. (2018), and Meya and Suntheim (2014) by focusing on student mobility programs' impact on student academic performance. It addresses a gap in the literature, which is the study of the temporal dimension of exchange programs (i.e., timing and duration), parameters that policymakers can adjust to increase efficiency. Even though the academic literature already acknowledges the temporal dimension of exchange programs[6], to the best of our knowledge, no studies asked whether there is a best moment or duration of a student mobility experience to increase students' performance.

[6] An example is the report from the European Commission developed by Rodrigues (2013), where the author identified heterogeneous effects on career outcomes depending on the duration of the mobility experience.

3. Data

This section details the data used for this paper. We first describe the empirical setting of the research, followed by a summary and description of the variables used in the analysis.

3.1. Empirical Setting

Our sample comprises 11,432 students from the University of Campinas (UNICAMP), Brazil, from 2010 to 2020. UNICAMP is a well-known research-intensive university that stands out in the Brazilian higher education system. In 2019, it was among the best Brazilian universities evaluated by the Brazilian Ministry of Education (Brasil, 2020a). According to the Times Higher Education Latin America ranking, it was ranked third among Latin American universities in 2020 (THE, 2020). The university is located in São Paulo state, the Brazilian state with the highest Gross Domestic Product in the country (Brasil, 2020b). The choice for UNICAMP is because the university has broad experience with internationalization activities (such as international cooperation and student mobility). Since its foundation in the 1960s, internationalization has been part of its primary institution strategy (Granja and Carneiro, 2020).

For the Executive Director of International Affairs at UNICAMP, internationalization has become imperative for institutions linked to science as societies become more connected: "We are in a phase of humanity where we face problems that belong to everyone. Climate change, extreme phenomena, disasters, management of increasingly scarce natural resources, diseases that are spreading across the planet. Science has become global because society has become global and the economy has become global – for better and for worse. If the university wants to honor its commitment to transmit knowledge to society, it needs to be international." (UNICAMP, 2020, para. 4)[7]. In the view of the university postgraduate dean, internationalization is essential to bring new themes, new technologies and methodologies, in addition to promoting what is done in the country (UNICAMP, 2020).

UNICAMP offers a varied range of exchange programs to its students, both at the undergraduate and postgraduate levels. Even though the selection criteria and the activities planned abroad are overall similar, programs have different nature and settings. In addition to the mobility carried out via agreements with foreign institutions to exempt tuition fees (the majority aimed at undergraduate students), UNICAMP also participates in programs financed by either private or public agencies, such as the Santander private bank, the Association of Universities of the Montevideo Group (AUGM) and the Brazilian Ministry of Education.

[7] Quote translated from Portuguese by the authors.

Between 2010 and 2017, the university had more than 500 agreements with foreign institutions, covering more than 60 countries (Granja, 2018). A part of those agreements was fostered by the university's participation in Science without Borders, a program created by the Brazilian federal government that took place between 2011 and 2015. Additionally, some university courses, such as engineering, also offer the possibility of taking a double degree at foreign universities. The exchange duration varies depending on the university's agreements with the host university and the external funding agency, but they usually last between one semester and two years.

Given its tradition of internationalization and the program variety, the number of UNICAMP students in mobility programs in the previous decade was elevated. Of the 11,432 students considered in this study, 1,943 participated (at least once) in an institutional student mobility program (17% of the entire sample), while 9,489 were in the nontreated (nonparticipants) group.[8] Students' academic, demographic, and socioeconomic information was shared directly by the UNICAMP's Academic Board and International Office after the approval of the Brazilian Research Ethics Committee[9].

Even though higher education institutions are very heterogeneous in Brazil, differing by size and type (public/private), the choice for UNICAMP also allows us to generalize our results to the Brazilian context. According to Schwartzman et al. (2021), UNICAMP is part of 16 large research-intensive public universities in Brazil with more than 30 thousand students, which accounted for 8% of total enrolment in 2018. Although not representative of the Brazilian higher education students, those universities are the ones that usually offer most study opportunities abroad. For instance, for the Science without Borders program, out of the top 10 home institutions, nine were in the same category as UNICAMP (Brasil, 2016). Considering the involvement of UNICAMP in the mobility programs, we are confident that our sample is representative of Brazilian exchange students.

3.2. Variables

The main dependent variable of this paper is students' academic performance, measured by the grades achieved in the university undergraduate program. Specifically, as an academic performance measure, we consider the standardized Performance Coefficient of the last semester students attended university. At UNICAMP, grades are calculated on a scale of 0 to 1, with 1 being the maximum grade. The grade for a semester is the average of the grades obtained in the course subjects taken during that semester, weighting by the course load (credits). The resulting aggregated grade is called Performance Coefficient.

[8] The dataset structure did not allow us to capture students who travelled outside an institutional mobility program, as only those who were properly registered for an exchange at UNICAMP were categorized as mobility students. Therefore, this paper focuses only on the impact of exchange programs under the management of the university.

[9] Protocol number 25285919.6.0000.8142.

Since undergraduate courses and course subjects have different difficulty levels, all grades used in the analysis were standardized by course and year of admission at the university. The standardization strategy is helpful to compare students from different cohorts and courses, and it is also widely used by UNICAMP in recruitment processes (for exchange scholarships, for instance) since it makes clear whether students' grades fall below or above their cohort average.[10]

Our final sample includes students who met one of the following criteria: 1) students who completed their courses; 2) students who abandoned university or did not renew their registration; and 3) students who were dismissed from the university (e.g., due to insufficient grades or low progression). For students who felt into criteria 2 or 3, we considered the standardized Performance Coefficient of the last semester attended before quitting the university. We included them in our sample since the decision to drop a course is often the result of obtaining low grades, and excluding them might determine a selection problem. As robustness check, we run our analysis on the subsample of students who completed their courses (students satisfying the first criterion only).

Students who were still enrolled at the end of our observation period and those who requested to transfer to a different university/course before their graduation were not considered. To ensure that each student was considered only once in the sample, only students registered for only one undergraduate course (i.e., did not do more than one program at UNICAMP) were considered in the analysis. Moreover, due to the lack of complete information on non-regular students, only those who entered university through the regular selection process (through an entrance exam) were considered.[11]

Figure 1 shows the distribution of the grades for the last semester at university for mobility students (also referred to from now on as the treatment group) and non-mobility students (nontreated or nonparticipants group). As we can observe, students who participated in international mobility programs had higher final grades than the nonparticipants. However, those differences cannot yet be attributed only to participation in mobility programs, as discussed later in this paper.

[10] The Standardized Performance Coefficient (SPC) formula is SPC = (PC - PCM) / SD, where PC is the Performance Coefficient of the student; PCM is the mean of the PC of the student's class; and SD is the standard deviation of the Performance Coefficient of the student's class. It is important to highlight that there is a small difference between our calculation of the Standardised Performance Coefficient and the one officially used by UNICAMP in recruitment processes. This is because the university standardizes the grades by class (i.e., students who share the same starting year, course, and group). Since the dataset shared by them does not allow us to have the information on the group that students studied (only year and course), we standardized using the variables available. Therefore, in this paper, students' grades are compared with the mean PC of those who joined the same course in the same year, but not necessarily were taking the courses in the same class with the same teachers.

[11] Removing those students should not bias our results, as the proportion of students registered for more than one course, as well the proportion of those who entered university through a non-regular selection process is small (less than 10% in both cases).

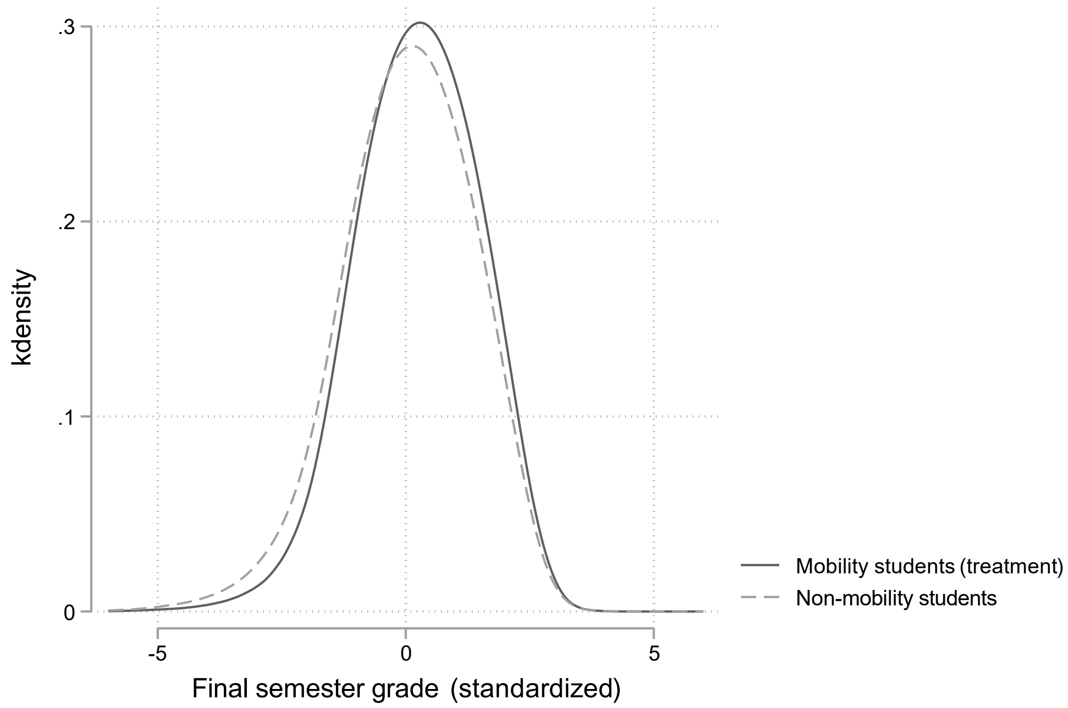

Figure 1: Dependent variable kernel density (mobility vs. non-mobility students)
Source: Authors' estimation from UNICAMP's microdata.

Table 1 lists all the variables included in our analysis with a short description. The rationale for the choice of the independent variables is explained in detail when discussing the empirical strategy.

Table 1 – Variable description

Variable	Measure
Dependent variable	
Grade last semester (standardized)	The Performance Coefficient that the student has received in the last semester that they attended their undergraduate program (before graduating or leaving university), standardized by course and year of admission in the university
Independent variables	
Participation in an international mobility program	1 if the student participated in an institutional international mobility program and 0 otherwise
Gender	1 if the student was female and 0 otherwise
Race/Skin color	1 if the student self-declared as black, brown or indigenous and 0 otherwise
Age	Age when entering university
Income per capita of household before entering university (in minimum wages)	1 if the per capita income was higher than the media of the sample (i.e., top 50^{th} percentile) and 0 otherwise*
Education of the parents	1 if at least one of the parents had access to university (regardless of obtaining a university degree) and 0 otherwise
Previous internal mobility experience	1 if the student completed high school outside São Paulo (Brazilian state where UNICAMP is located)
Student's pre-university academic ability	Grade in the university entrance exam, standardized by course and year of admission in the university
If eligible for the Science without Borders (SwB) program	*Eligible year:* 1 if the student started university at least one year before the SwB program was cancelled *Eligible area:* 1 if the student was enrolled in Biological Sciences, Health, Exact, Technological or Earth Sciences courses (main areas of the SwB program)

Note. *To calculate this variable, the household income was divided by the total number of people in the household. If the total number of people in the household was unknown, the mean of the dataset was used (3.8 people in a household).

Table 2 shows the summary statistics for our sample of students. Not surprisingly, treated and nontreated students differ significantly in all baseline characteristics. Mobility students have, on average, better academic performance both before and during university. They also have, on average, higher incomes (55% were in the top 50^{th} income percentile when entering university) than the students who do not participate in any institutional mobility program (45%). Moreover, mobility students have more educated parents than the non-mobility group (71% and 60%, respectively).

There are also other differences regarding the composition of the groups. For example, females represent 46% of exchange students and 49% of non-exchange students. Black/brown/indigenous students are 11% of the mobility sample and 14% of the non-mobility one. Mobility students also have more previous internal mobility experience and are one year younger than nonparticipants when entering university. Those figures suggest self-selection in the sample, meaning that participants and nonparticipants would differ even in the absence of treatment (Caliendo and Kopeinig, 2008). The self-selection challenge is well-known in empirical studies assessing the impact of mobility programs (Meya and Suntheim, 2014) and will be discussed in the next section.

Table 2: Summary statistics of participants and nonparticipants

	Total			(1) Participants (Mobility students)			(2) Nonparticipants			t-value (1) vs. (2)
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	
Grade last semester (standardized)	9340	.076	.881	1749	.235	.759	7591	.04	.903	8.400***
Grade first semester (standardized)	11432	.104	.886	1943	.504	.699	9489	.022	.898	22.280***
Student's pre-university academic ability (standardized grade in the entrance exam)	11432	.013	.983	1943	.288	1.029	9489	-.043	.964	13.630***
Income per capita of household before entering university (if top 50th percentile)	11432	.469	.499	1943	.552	.497	9489	.451	.498	8.090***
Education of the parents (if parents had access to tertiary education)	11432	.62	.485	1943	.706	.456	9489	.603	.489	8.590***
Gender (if female)	11432	.487	.5	1943	.461	.499	9489	.492	.5	-2.520**
Race/Skin color (if black, brown or indigenous)	11432	.137	.344	1943	.108	.311	9489	.143	.35	-4.040***
Age when entering university	11432	19.951	3.141	1943	19.127	1.372	9489	20.12	3.366	-12.780***
Previous internal mobility experience	11432	.133	.34	1943	.172	.378	9489	.125	.331	5.620***
Year eligible for the SwB program (if yes)	11432	.901	.299	1943	.976	.152	9489	.885	.318	12.290***
Area eligible for the SwB program (if yes)	11432	.668	.471	1943	.76	.427	9489	.649	.477	9.480***

Source: Authors' estimation from UNICAMP's microdata.

Note. Not all students had their final semester grades available in the dataset since not all the students were enrolled in courses in their last semester. Even though those students were not considered when calculating the difference-in-difference models, they were included when calculating the propensity scores so that the probability of participating in an exchange program was more precisely calculated. *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

4. Empirical strategy

To reduce the possible bias due to the selection of mobility programs (e.g., self-selection and targeting), the methodology chosen for the analysis is a combination of Propensity Score Matching (PSM) and Difference in Differences (DiD).

Propensity Score Matching is a very flexible statistical technique used for impact evaluation that can be applied in the context of almost any program, as long as there is a group of nontreated units (Gertler et al., 2016). It compares units with a similar probability (propensity score) of receiving a specific treatment (Caliendo and Kopeinig, 2008; Gertler et al., 2016). Since baseline data on our outcome of interest (student performance) was available, we decided to combine the matching with Difference in Differences, a method that compares the changes in outcomes over time between treated and nontreated units (Gertler et al., 2016). The advantage of combining both methodologies is to reduce bias in the results since the combination solves the issue of any unobserved characteristic that is constant across time between the two groups (Caliendo and Kopeinig, 2008; Gertler et al., 2016).

The combination of PSM and DiD is the best possible methodology that could be used in our setting. The rationale for using quasi-experimental methods is mainly because doing an experimental framework (such as a Randomized Control Trial), where students are randomly assigned to study abroad, is not feasible in this case. Moreover, since at UNICAMP there is no threshold at which students become automatically eligible to participate in student mobility, empirical strategies like regression discontinuity designs also cannot be applied (Meya and Suntheim, 2014). In fact, UNICAMP has several different mobility programs, and students are not restricted to only applying to one of them.

The control group for the analysis was created using Propensity Score Matching. To identify potential mobile students, we considered as relevant matching characteristics the following: student's demographic and family characteristics, previous internal mobility experience, students' academic performance, and access to study abroad scholarships. To ensure that none of the variables could be affected by having participated in mobility programs (therefore biasing our results)(Gertler et al., 2016), all variables included in the propensity score calculation are either time-invariant or measured before any mobility could occur.

We considered gender, age when entering university, and race/skin color as students' demographic characteristics. Those variables were added to account for any possible systematic differences between students with different demographic characteristics concerning their choice of going abroad and their academic performance.

As family's characteristics, we included the income per capita of their household before entering university and their parent's education. Those two variables were added to account for students' socioeconomic background since students from higher-income families may be more likely to pursue part of their studies abroad (Brandenburg et al., 2016; Junor and Usher, 2008; Meya and Suntheim, 2014). Additionally, first-generation college students have many responsibilities that compete with the university for time and attention, such as working full-time or being married (Eveland, 2020; Warburton, Bugarin and Nuñez, 2001). Parent's education was also added to account for social capital, as highly educated parents might support an exchange not only financially but by highlighting the benefits of learning about other countries, languages, and cultures (Di Pietro, 2019; Meya and Suntheim, 2014).

Previous internal mobility experience was added because such an experience might affect students' final grades. For example, students who have already left their social environment once may be more likely to go to another country and spend more effort finding the perfect match regarding university and field of study (Meya and Suntheim, 2014).

As students' academic performance, we added the grades in the first semester of university[12] and grades in the entrance exam. Academic performance at the university is the most important criterion considered by UNICAMP to select exchange students. Grades in the entrance exam were also added to account for students' pre-university academic ability, as students who apply for mobility programs may be academically more able than others. Thus, pre-university grades may predict university success and measure students' commitment (Meya and Suntheim, 2014).

Finally, we also accounted for access to scholarships to go abroad. During 2011 and 2015, as already mentioned, the Brazilian government implemented a massive exchange program called Science without Borders, which sent more than 90 thousand Brazilians to study abroad (Brasil, 2016). Since the program offered more scholarships for students in selected areas (e.g., Biological Sciences, Health, Exact, Technological, and Earth Sciences) that entered university between 2010 and 2014, dummies to account for the year of admission and area of the course were added.

We explore the impact of student mobility programs on student academic performance as measured by the average treatment effect on the treated (ATT) students, i.e., those who benefited from a mobility program. The ATT for our main outcome variable before and after participation (ΔY) can be formally specified as follows:

$$ATT = E(\Delta Y^T | D = 1) - E(\Delta Y^C | D = 0) \quad (1)$$

where Y^T denotes the potential grades for the treated individuals; Y^C denotes the potential grades for the nontreated individuals; D is a dummy variable for student mobility status; and E() denotes the mathematical expectation operator.

Our model was given by:

$$Y_{it} = \beta_1 + \beta_2 treatment_i + \beta_3 time_i + \gamma(treatment_i * time_i) + X_i + \varepsilon_{it} \quad (2)$$

Where Y_{it} stands for grades of student *i* at time *t*; treatment is a dummy variable that takes the value of 1 if student *i* participated in a student mobility program; *time* is a dummy variable that takes the value of 1 at the end of the student's *i* course; *treatment*time* is the interaction between the treatment variable

[12] Since students can apply for mobility and travel in different periods of their undergraduate courses, and since the data shared by the university did not allow us to capture the grade immediately prior to the application for mobility, only the first semester of university was considered as baseline university grade. The grade in the first semester was registered prior to any student mobility, therefore not affected by the participation in mobility programs.

and time; X_i is a set of individual pre-treatment covariates of student *i* in time *t* = 0; and ε_{it} is the error term. γ is calculated by the DiD model and represents the average treatment effect. To combine DiD with PSM, the regression used weights derived from the Kernel Propensity Score Matching, predicted through the following equation.[13]

$$E(treatment|X) = P(treatment = 1|X) \quad (3)$$

Where *treatment* is a dummy variable that takes the value of 1 if the student participated in a student mobility program; X is a set of individual pre-treatment covariates, and E() denotes the mathematical expectation operator.

4.1. Propensity Score Matching Assumptions

When using Propensity Score Matching for an impact evaluation, two assumptions should be examined: the Conditional Independence and the Common Support, both discussed below.

4.1.1. Conditional Independence (CI)

The Conditional Independence assumption (also called unconfoundedness or selection on observables) states that differences in outcomes (Y) between treated (T) and comparison (C) individuals with the same values for pre-treatment covariates (X) are attributable to treatment (D)(Caliendo and Kopeinig, 2008). In other words, it says that conditional on X, (Y_T, Y_C) and D are independent. The X vector should be composed of variables measured before participation or unaffected by the program (e.g., time-invariant variables) to avoid possible biased results (Gertler et al., 2016). The CI assumption can be written as follows:

$$(Y_T, Y_C) \perp\!\!\!\perp \mathrm{D} \mid \mathrm{X} \quad (4)$$

where $\perp\!\!\!\perp$ denotes independence.

The main challenge with the CI is that it is a very strong assumption, and it cannot be tested. Since it is crucial to match based on the characteristics that determine participation, it is essential to understand the criteria used for participant selection (Gertler et al., 2016). In the case of our sample, we believe that the most important pre-treatment characteristics to determine participation in mobility programs were included in our model. At UNICAMP, the selection criteria for student mobility programs are overall

[13] Kernel algorithm uses weighted averages of all individuals in the control group to construct the counterfactual outcome. Weights depend on the distance between each individual from the control group and the participant observation for which the counterfactual is estimated (Caliendo and Kopeinig, 2005).

well established, as mobility students must: 1) be a regular student at the university; 2) have completed between 25% and 85% of the course load at the time of application and attended at least two semesters in their undergraduate program; 3) have a 'profile of excellence,' based on good academic performance; 4) have the application approved by the course coordinator; 5) meet the requirements requested by the destination institution.

Criteria 1 and 2 were met for all students in the dataset, as all of them were regular, started university before 2018, and completed at least their first year at university. Criterion 3 was measured by the grade in the 1st year of university and the student's pre-university academic ability (i.e., grades in the entrance exam). Criterion 4 was not directly observable, as there was no feasible way to know if the coordinator would have approved the application of a non-mobility student if they had asked for it. Therefore, we assume that the coordinator's approval was conditional on good academic performance. Criterion 5 varies from student mobility programs but usually relies on academic performance.

Since Criteria 4 and 5 were not directly observed in our dataset, we tried to account for other possible 'hidden' criteria that may have affected both participation and the outcome of interest by adding socioeconomic and demographic variables in the model. Even if they were not directly considered in the selection process, they might still have affected students' motivation to apply for an exchange program. They could also be related to students' final grades. Besides, those characteristics could also have indirectly affected the course coordinator's approval (for instance, if there was any prejudice in the selection regarding skin color, gender, or socioeconomic status). To finish, we also added two variables to account for eligibility to the Science without Borders program since those eligible students had more choices of scholarships and destination countries.

Additionally, as discussed before, we combined PSM with DiD, to account for any possible selection based on time-invariant unobservables (Caliendo and Kopeinig, 2008). Therefore, grades in the last semester were compared with those in the first semester of university, when students are still not eligible to apply for any institutional mobility program. By adding all those variables and combining methodologies, we are confident that we have controlled for characteristics that might have impacted both the assignment to the treatment and the outcome variable.

4.1.2. Common Support

The second assumption of PSM is called common support (or overlap). For propensity score matching to produce estimates of a program's impact for all treated observations, each treatment unit must be successfully matched to a nontreated unit (Gertler et al., 2016). In practice, however, it may be that for some treated individuals, there is no untreated with a similar propensity score (which is called lack of common support) (Gertler et al., 2016). The common support assumption says that persons with the same characteristics (X) have a positive probability (P) of being both participants and nonparticipants of the program (Heckman et al., 1999). The assumption can be written as follows:

$$0 < P(D = 1|X) < 1 \tag{5}$$

Several ways are suggested in the literature to validate this assumption. However, the most straightforward one is a visual analysis of the density distribution of the propensity score in both groups (Caliendo and Kopeinig, 2008). Figure 2 shows the distribution of the propensity scores for both the treatment and control groups in the sample. As expected, treated units had their distribution of propensity scores more skewed to the left, while the controls were more skewed to the right. The graph shows that the common support assumption was satisfied, with 99.8% treated observations within the common support area.

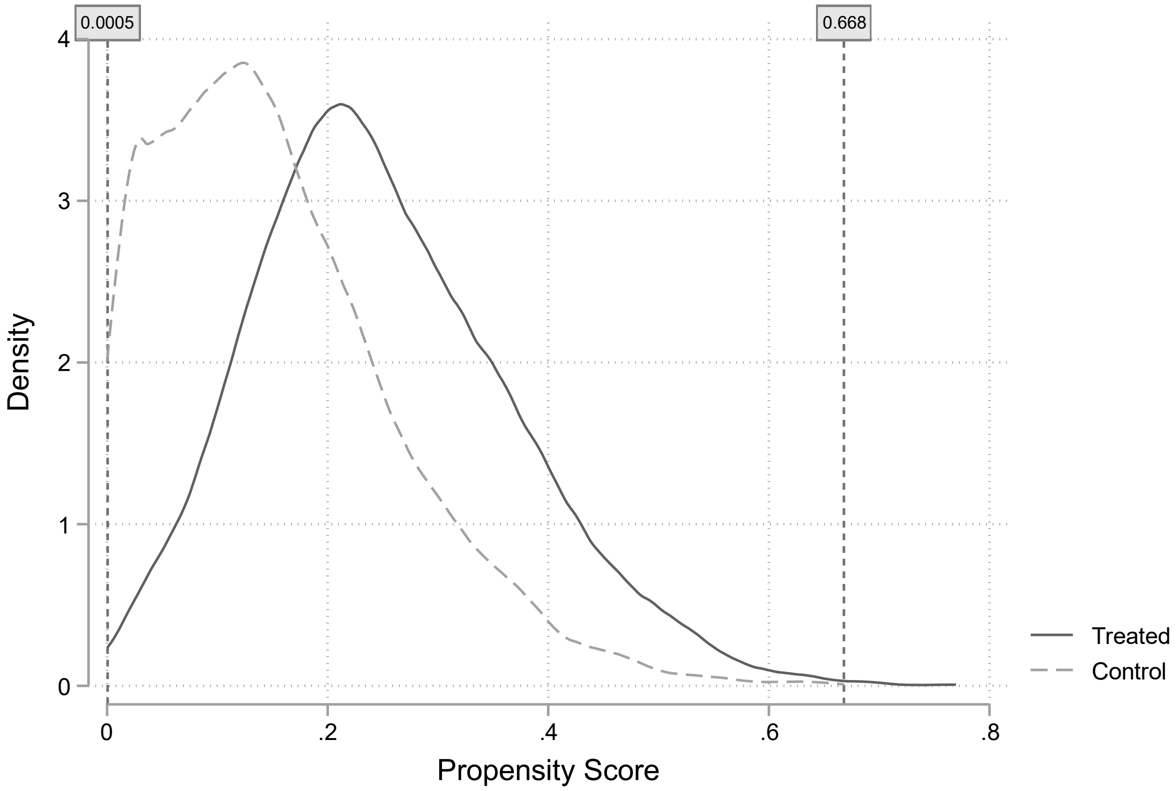

Figure 2 – Distribution of the propensity scores for treatment and control groups (Common Support Assumption)
Source: Authors' estimation from UNICAMP's microdata.

5. Results and Discussion

This section shows the main results of our analysis, including the disaggregation of the results for different subgroups. It also discusses the findings and suggests possible mechanisms explaining the causal relationship between the treatment and our outcome of interest. Finally, the section also includes a test for the balancing property after matching and a set of robustness checks.

5.1. Probit model results

Table 3 shows the probit model results used to predict the propensity score (Equation 3). In the model, the dependent variable is a binary that took the value 1 if the student participated in an institutional mobility program in the period 2010-2020 and 0 otherwise. The independent variables used are those listed in Table 1.

The results show that all variables, except for skin color and age, significantly impacted the probability of participating in a student mobility program. Higher grades in the entrance exam and in the first semester of university, high income per capita, more educated parents, previous internal mobility experience, and eligibility to the Science without Borders program are all associated with a positive effect on the conditional probability of being treated, holding all other regressors constant at their means. On the other hand, being female has a negative effect on the conditional probability of being in the treatment group.

Table 3 - Participation in Student Mobility Programs, Probit Results

Dependent variable: Pr(Student Mobility = 1)	Coefficients		Marginal Effects	
	Coef.	Std.Err.	Coef.	Std.Err.
Grade first semester (standardized)	0.384***	0.021	0.081***	0.004
Student's pre-university academic ability (standardized grade in the entrance exam)	0.076***	0.016	0.016***	0.003
Income per capita of household before entering university (if top 50th percentile)	0.164***	0.032	0.035***	0.007
Education of the parents (if parents had access to tertiary education)	0.136***	0.034	0.029***	0.007
Gender (if female)	-0.05*	0.03	-0.010*	0.006
Race/Skin color (if black, brown or indigenous)	-0.039	0.047	-0.008	0.010
Age when entering university	0.072	0.112	0.015	0.023
Age when entering university (squared)	-0.004	0.003	-0.001	0.001
Previous internal mobility experience	0.13***	0.042	0.027***	0.009
Year eligible for the SwB program (if yes)	0.846***	0.075	0.178***	0.015
Area eligible for the SwB program (if yes)	0.186***	0.033	0.039***	0.007
Constant	-1.923	1.179		
Number of observations	11432			
Pseudo r-squared	0.110			
Chi-square	840.470			
Prob > chi2	0.000			

Source: Authors' estimation from UNICAMP's microdata.

Note: Marginal effects calculated at the means of covariates. *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

5.2. Balancing test for PSM estimations

After estimating the propensity scores for each unit of our sample, we then tested the balancing property of each observed covariate between the treatment and control groups, as well as the overall balance. The idea is to verify if there was a reduction in sampling bias achieved through matching.

The results presented in Table 4 indicate that there was indeed a reduction in the bias after matching. The first part of the table shows that the matching sufficiently balanced most observable covariates and reduced considerably initial differences of both treated and untreated. The second part of the table shows the results from comparing the joint significance of all matching variables in the probit model. The Pseudo R-squared of results after matching was much lower for the matched sample than for the unmatched one. Both the mean and the median of the absolute standardized bias have been reduced substantially. Additionally, Rubins' B (the absolute standardized difference of the means of the linear index of the propensity score in the treated and nontreated group) and Rubin's R (the ratio of treated to nontreated variances of the propensity score index) felt within the bounds suggested by Rubin (2001). Those results indicate that the samples became sufficiently balanced after matching.

Table 4 - Balancing results before and after matching

Variable	Sample	Mean		Bias (%)	t-test	
		Treated	Control		t	p>t
Grade first semester (standardized)	Unmatched	.50378	.02244	59.8	22.28	0.000
	Matched	.5006	.42887	8.9	2.87	0.004
Student's pre-university academic ability (standardized grade in the entrance exam)	Unmatched	.2882	-.04293	33.2	13.63	0.000
	Matched	.2829	.21619	6.7	1.87	0.062
Income per capita of household before entering university (if top 50th percentile)	Unmatched	.55172	.45147	20.1	8.09	0.000
	Matched	.55155	.53049	4.2	1.22	0.223
Education of the parents (if parents had access to tertiary education)	Unmatched	.70612	.60259	21.9	8.59	0.000
	Matched	.70619	.68727	4.0	1.19	0.235
Gender (if female)	Unmatched	.46063	.49204	-6.3	-2.52	0.012
	Matched	.46134	.48597	-4.9	-1.42	0.155
Race/Skin color (if black, brown or indigenous)	Unmatched	.10808	.14259	-10.4	-4.04	0.000
	Matched	.10825	.1129	-1.4	-0.43	0.669
Age when entering university	Unmatched	19.127	20.12	-38.6	-12.78	0.000
	Matched	19.128	19.221	-3.6	-1.88	0.060
Age when entering university (squared)	Unmatched	367.71	416.13	-33.8	-10.88	0.000
	Matched	367.76	371.62	-2.7	-1.88	0.061
Previous internal mobility experience	Unmatched	.17241	.12499	13.4	5.62	0.000
	Matched	.17165	.15666	4.2	1.16	0.245
Year eligible for the SwB program (if yes)	Unmatched	.97633	.88545	36.4	12.29	0.000
	Matched	.97629	.96758	3.5	1.54	0.125
Area eligible for the SwB program (if yes)	Unmatched	.75965	.64886	24.5	9.48	0.000
	Matched	.75928	.72981	6.5	1.95	0.051

Sample	Pseudo R-squared	LR chi^2	p>chi^2	Mean Bias	Median Bias	B	R
Unmatched	0.110	1150.93	0.000	27.1	24.5	77.2*	0.29*
Matched	0.004	20.75	0.036	4.6	4.2	15.9	1.07

Source: Authors' estimation from UNICAMP's microdata.
Note. * if B>25%, R outside [0,5; 2]

5.3. Impact of mobility programs on academic performance

Results from the Kernel-based propensity score matching difference in differences (Table 5) show that, overall, participation in international student mobility programs does not significantly increase students' standardized final grades.

As already stated in Section 2, most existing studies on the impact of academic mobility find that students benefit from mobility programs. However, there is no full convergence of results in the literature in terms of the impact on grades. While authors such as Meya and Suntheim (2014) find that a brief study-related visit abroad significantly increases students' final grades, Czarnitzki et al. (2021) show evidence that, on average, exchange students experienced a grade decrease. However, authors agree in the fact that the impact of a mobility program on students is context-specific, not always homogeneous across the mobility programs and students' characteristics (Contu et al., 2020; Czarnitzki et al., 2021; Di Pietro, 2013; Gonzalez-Baixauli et al., 2018; Parey and Waldinger, 2011; Sorrenti, 2017).

For that reason, the next subsections investigate possible heterogeneous impacts of student mobility programs in academic performance across different subgroups of students. Two main questions guide our analysis: 1) does the impact vary across students traveling in different periods of their undergraduate courses? (i.e., is there a best moment to participate in student mobility?); 2) does the impact vary across programs with different durations? (i.e., is there a best duration of a student mobility experience?). Additionally, we also investigate possible economic and demographic heterogeneous effects and effects related to the destination region.

Table 5: Average treatment effect on the treated

	(I)	(II)	(III)
Dependent variable: Final grade	0.010 (0.021)	0.012 (0.020)	0.006 (0.020)
Untreated	9489	9489	9489
Treated	1940	1940	1940
Included the covariates of the PSM model	No	Yes	Yes
Included control for year of admission at university	No	No	Yes
Included control for undergraduate course	No	No	Yes

Source: Authors' estimation from UNICAMP's microdata.

Note. Kernel-based propensity score matching difference in differences estimation; standard errors in parentheses; average treatment effect calculated using the DIFF and the PSMATCH2 packages for Stata; only observations on common support are used; propensity score matching calculated using kernel bandwidth of 0.06; column (I) shows the results of the difference in differences estimation without covariates; column (II) shows the results of the difference in differences estimation including all the covariates used to estimate the propensity score (except for grades in the first semester); column (II) shows the results of the difference in differences estimation including all the covariates used to estimate the propensity score (except for grades in the first semester) and also controls for year of admission and course; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

5.3.1. Is there a best moment for participating in a student international mobility program?

To answer the first question, we disaggregate the effects of student mobility into three different types of students, based on the time of the mobility experience (measured by the time elapsed between the starting year at the university and the year of the first mobility).

In Brazil, most undergraduate programs last for eight semesters (4 years), which may vary according to the schedule offered by the institution and upon request for extension. Based on the structure of Brazilian undergraduate programs, we identify three types of students:

- Type I: students who traveled at the beginning of their undergraduate studies. UNICAMP does not allow students to participate in international institutional mobility during their first year, and considering that just a few students traveled between the first and the second year (Figure 3), those that attended university for one or two years before mobility were considered as Type I.

- Type II: students who traveled in the middle of their undergraduate studies (3 years after starting university)
- Type III: students who traveled closer to the end of their undergraduate studies (more than three years after starting university)

Figure 3 shows the distribution of the students in our sample by the number of years before the first international mobility, indicating that most of the students at UNICAMP traveled between the second and the third year after they started university.

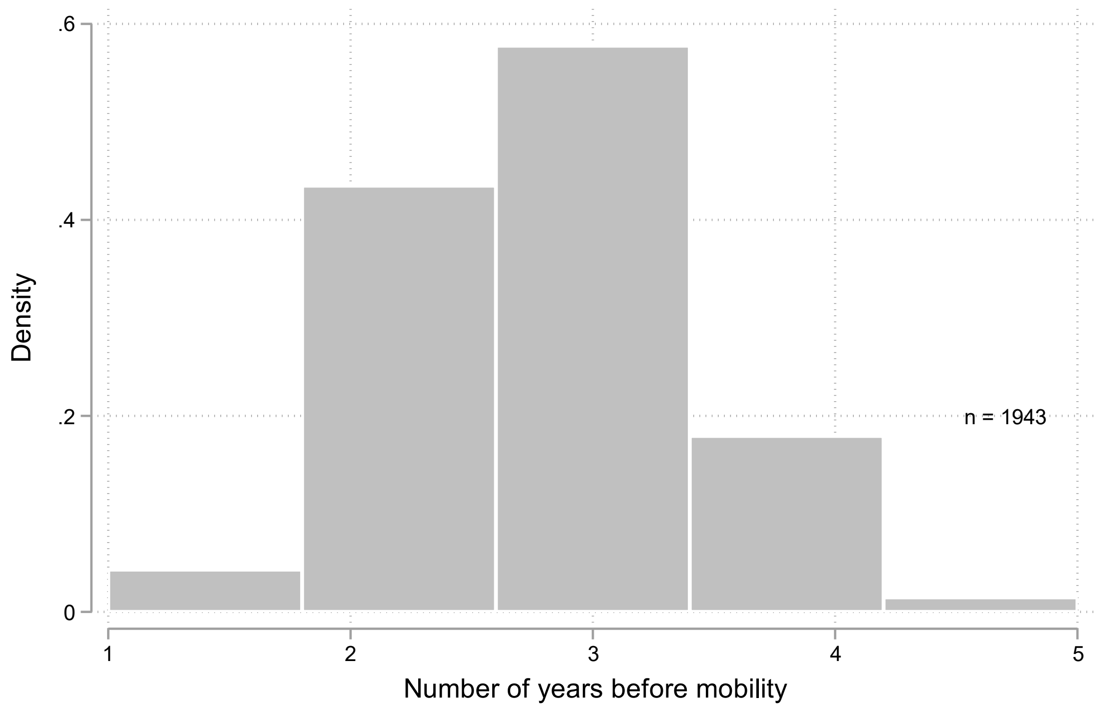

Figure 3: Distribution of students by the number of years before the first mobility (mobility students only)
Source: Authors' estimation from UNICAMP's microdata.

Considering the above three student types, Table 6 reports the results from the kernel-based propensity score matching difference in differences analysis. While negative effects on grades are found for those who traveled at the beginning of university (-0.05 points), positive and significant effects are found for students who traveled closer to the end of their courses (0.06 points). Those results suggest that the time of mobility matters when it comes to increasing final grades.

Table 6 - Average treatment effect on the treated by student type (students who traveled at the beginning of the university, in the middle or at the end of their courses)

	Beginning of the course (Type I)	Middle of the course (Type II)	End of the course (Type III)
Dependent variable: Final grade	-0.048**	0.033	0.062***
	(0.021)	(0.021)	(0.022)
Untreated	9489	9489	9489
Treated	755	878	307

Source: Authors' estimation from UNICAMP's microdata.

Note. Kernel-based propensity score matching difference in differences estimation; standard errors in parentheses; average treatment effect calculated using the DIFF and the PSMATCH2 packages for Stata; only observations on common support are used; propensity score matching calculated using kernel bandwidth of 0.06; the model includes all the covariates used to estimate the propensity score (except for grades in the first semester) and also controls for year of admission and course; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

At UNICAMP, the grades obtained abroad are registered as proficiency, therefore not incorporated into the student's Performance Coefficient. This rule guarantees that differences in grades are due to changes in students' performances and not to different grading systems at the host institututions. With that in mind, a possible explanation for our results can be found into students' behaviour. Students in their first years of university are still adapting to university life, taking more courses, learning about their courses' challenges, and familiarizing themselves with their peers. By traveling at the beginning of their courses, students may suffer from a twofold adaptation challenge, i.e., adapting to university and adapting to a different country.

Moreover, traveling before being wholly integrated to their home universities may impose difficulties in re-entering the home education system when returning, impacting performance on exams. On the contrary, those who travel closer to graduation are older and may have a more mature mindset. Those students are already more integrated into university life and most likely have a clearer idea of what they expect from their degrees, which may affect their grades positively.

While UNICAMP's data does not allow testing this hypothesis empirically, anecdotal data help support it. According to a Type I student from our sample, a bad experience abroad had a crucial negative impact on their adaptation after returning:

> "I ended up having the worst grades of my life during the exchange program. (...) some colleagues tried to convince me that it was not so bad, but I was super dissatisfied. I came back a little frustrated, I guess. I traveled during my best moment and then when I came back, I had to face some insecurities like 'maybe I am bad, dumb, weak (...)'. I returned and did only four courses, a low number compared to what I was used to, and still got a score below 8 [out of 10], which was also completely atypical. (...) it was generally being a difficult semester. The return of the exchange also affected my friendships, my mood, it was a combo."[14]

[14] All quotes in this paper were translated and adapted from Portuguese by the authors.

While the choice of the cutoffs for distinguishing the tree types of students was based on the structure of undergraduate courses in Brazil, in the Robustness checks section (Section 6), we report a sensitivity analysis of our results to our cutoff choice.

5.3.2. Is there a best duration for a student international mobility program?

To answer the second question, we disaggregated the effects into three different mobility types based on the duration of the mobility program (measured by the time elapsed between the starting and the ending date of the exchange period)[15]. The thresholds were chosen based on the structure of the courses at UNICAMP, where the academic year is split into two academic semesters. Consequently, the majority of the academic activities in the university (such as internships, courses and most exchange programs) are offered for at least one academic semester. We considered the following three types of students:

- Type A: students who experienced short-term mobility (up to one semester)
- Type B: students who experienced mid-term mobility (one semester to one year)
- Type C: students who experienced long-term mobility (more than one year)

Figure 4 illustrates the distribution of students in our sample by the total mobility duration and indicates that most of the students at UNICAMP stayed abroad for a period close to 12 months (two semesters).

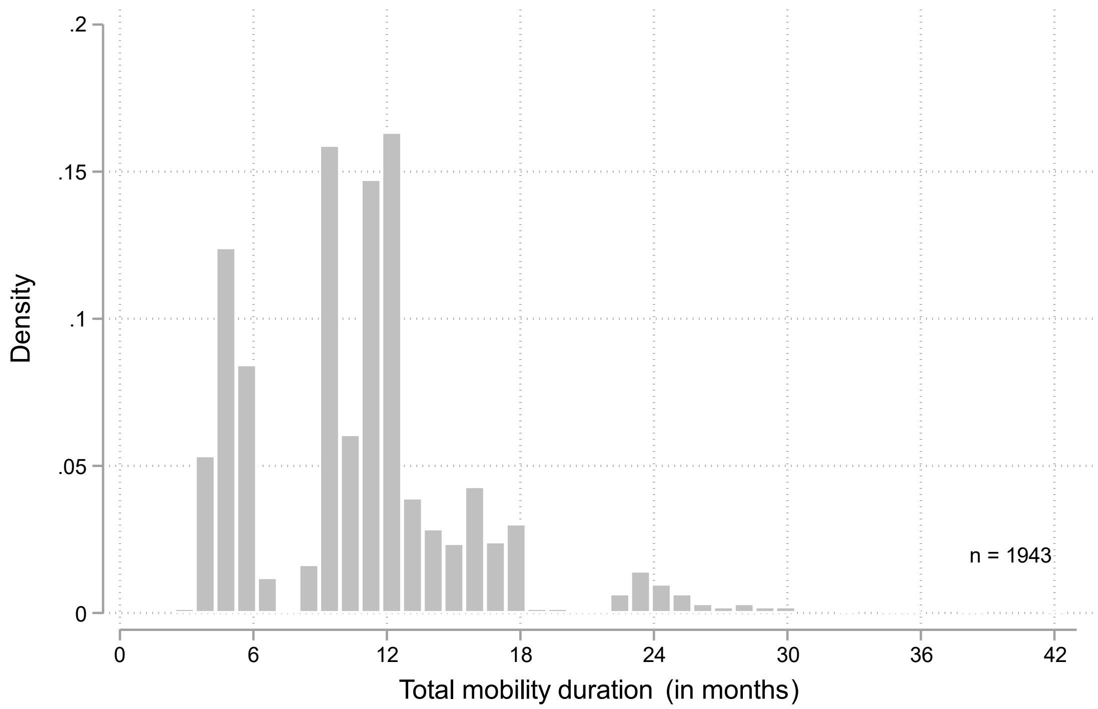

Figure 4 - Distribution of students by mobility duration (in months)
Source: Authors' estimation from UNICAMP's microdata.

[15] If the student participated in more than one mobility program, all the periods were added together.

Results from the estimations (Table 7) indicate that while international mobility positively and significantly impacted students who participated in programs lasting from one semester to one year, negative effects were associated with shorter periods abroad. That suggests that the period of mobility also plays a role in academic performance. On average, students who participated in mid-term programs experienced an increase in their final grades of 0.08 points, while students spending shorter periods abroad had a decrease of 0.1 in their last semester grades. No evidence of impact was found for students in long-term programs.

Table 7 - Average treatment effect on the treated by student type (students who stayed abroad for a short, mid-term, or long period)

	Short-term (Type A)	Mid-term (Type B)	Long-term (Type C)
Dependent variable:	-0.099***	0.082***	-0.024
Final grade	(0.022)	(0.021)	(0.021)
Untreated	9488	9489	9489
Treated	497	912	531

Source: Authors' estimation from UNICAMP's microdata.
Note. Kernel-based propensity score matching difference in differences estimation; standard errors in parentheses; average treatment effect calculated using the DIFF and the PSMATCH2 packages for Stata; only observations on common support are used; propensity score matching calculated using kernel bandwidth of 0.06; the model includes all the covariates used to estimate the propensity score (except for grades in the first semester) and also controls for year of admission and course; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

Those results may be explained by the fact that short-period stays can distract students since adapting to a new country, and to a different higher education system, usually takes some time. Therefore, spending more time abroad gives students more chances to re-evaluate their own relationship with their courses, as stated by two Type B students from our sample:

> "After returning, a factor that positively influenced academic performance in other disciplines of the course was the contact I had abroad with other sub-areas of my course (which I would not have at UNICAMP), other ways of thinking about the content of the disciplines and also other more inclusive ways of building the teacher-student relationship."

> "It was a matter of 'commitment culture'. (...) I have never had too many problems with the courses at UNICAMP, but I was very uncommitted. (...) I returned from the exchange much more punctual and taking things more seriously. (...) I'm sure my grades went up."

While more extended stays may be needed if students want the benefits of mobility programs to enrich their academic curriculum, there seems to be a threshold where students stop benefiting from mobility (after one year). The nonsignificant impact of long-term programs could be related to the fact that students may face more challenges readjusting to their home universities after spending a long time abroad. However, more research is still needed to test those hypotheses empirically.

5.3.3. Other heterogeneous effects: economic/demographic and destination country

In addition to the subgroups described above, we also disaggregated the analysis by some pre-treatment economic and demographic variables, such as gender, skin color/race, parent's education, and income per capita (Table 8), and into region and language of the destination country (Table 9).

Our estimations suggested that, while there seem to be no differences between students coming from different economic and demographic settings, there are differences between students by destination countries.[16] A positive impact on grades was found for students traveling to North America (United States and Canada), Oceania (Australia and New Zealand), and English-speaking countries. In contrast, negative impacts were associated with students traveling to Portuguese speaking countries.

A possible reason for this result can be the correlation between destination country and mobility duration. As Figure 5 shows, a larger number of students who traveled to English-speaking countries experienced mid-term mobility. In contrast, those students who went to Portuguese-speaking countries experienced primarily short-term mobility. This correlation is due to the types of scholarships that UNICAMP provided in the period studied since the scholarships for Portugal were usually focused on short-term stays.

Table 8 - Average treatment effect on the treated: economic and demographic heterogeneous effects

	Gender		Skin color/race		Parent's education		Income per capita	
	Female	Male	Black, Brown or Indigenous	Otherwise	Less educated parents	More educated parents	Lower income per capita	Higher income per capita
Dependent variable: Final grade	0.009 (0.029)	0.005 (0.027)	0.018 (0.057)	0.004 (0.021)	-0.052 (0.033)	0.027 (0.025)	-0.045 (0.027)	0.041 (0.029)
Untreated	4669	4820	1353	8136	3771	5718	5205	4284
Treated	895	1045	210	1730	570	1370	870	1070

Source: Authors' estimation from UNICAMP's microdata.

Note. Kernel-based propensity score matching difference in differences estimation; standard errors in parentheses; average treatment effect calculated using the DIFF and the PSMATCH2 packages for Stata; only observations on common support are used; propensity score matching calculated using kernel bandwidth of 0.06; the model includes all the covariates used to estimate the propensity score (except for grades in the first semester) and also controls for year of admission and course; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

[16] The results in Table 9 are based on a subsample of students who had detailed information about their mobility programs in the dataset (1583 out of 1943 students). To be able to isolate the effects, students who had more than one region of destination, as well as those that traveled to more than one country with different languages were not considered.

Table 9 - Average treatment effect on the treated: region of destination

	Region of destination					Main language of destination country		
	Europe	Asia	Latin America	North America	Oceania	English	Portuguese	Spanish
Dependent variable: Final grade	-0.007 (0.021)	-0.008 (0.020)	-0.016 (0.022)	0.116*** (0.021)	0.138*** (0.021)	0.107*** (0.021)	-0.153*** (0.022)	0.032 (0.021)
Untreated	9489	9440	9479	9488	9477	9489	9471	9488
Treated	974	42	51	334	180	752	170	138

Source: Authors' estimation from UNICAMP's microdata.

Note. Kernel-based propensity score matching difference in differences estimation; standard errors in parentheses; average treatment effect calculated using the DIFF and the PSMATCH2 packages for Stata; only observations on common support are used; propensity score matching calculated using kernel bandwidth of 0.06; the model includes all the covariates used to estimate the propensity score (except for grades in the first semester) and also controls for year of admission and course; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

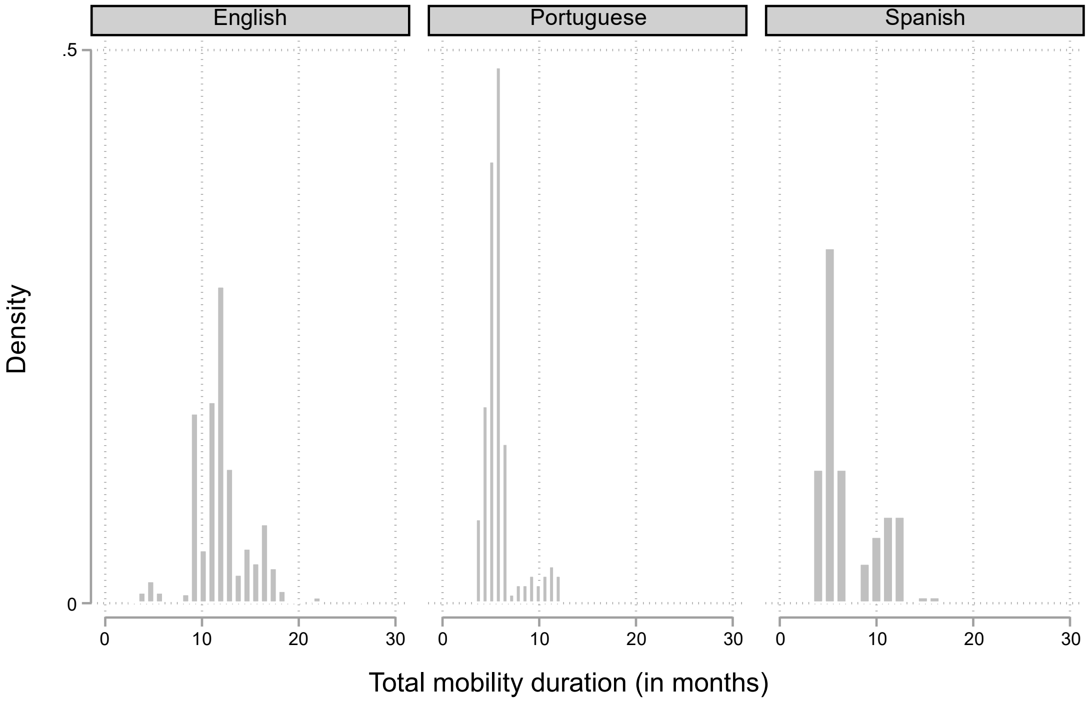

Figure 5 - Distribution of students by mobility duration and language of the destination country
Source: Authors' estimation from UNICAMP's microdata.

A second explanation to why the language of the destination country could impact students' grades is the potential role of foreign language training on students' cognitive development and academic achievement. In a review about the personal benefits of learning a different language, for instance, Weatherford (1986) stated that while it is already known that those familiar with a different language and culture can communicate more effectively with foreigners, it is also possible that through learning another language and culture, people become better problem-solvers. According to the author, foreign language study has the potential to aid and even accelerate the cognitive development of the brain, which could impact students grades in areas other than linguistics.

The discussion about the role of the country of destination and the selection of universities based on language skills is not new in the Brazilian literature on student mobility. For instance, in a study about the Science without Borders program at the University of Campinas, Granja and Carneiro (2020) mentioned the case of Portugal, saying that despite the preference of Brazilian students to study in Portuguese universities (at the earlier stages of the program one out of five fellows chose Portugal), public calls to the country were officially cancelled in the following years, when it became clear to policymakers that students were choosing Portugal due to the language. That is because applying for an exchange program to go to Portugal normally does not require knowledge of another language other than Portuguese (Brazil's official language). In contrast, calls for countries where Portuguese is not the primary language typically require proof of language proficiency.

Even though our data does not allow us to test analytically if the observed country heterogeneity is explained by the language spoken, data on English proficiency at entry in the university programs seems to confirm that those students who chose a Portuguese-speaking language destination country are those students who had lower grades in English in the university admission exam (Figure 6). They also had slightly lower grades in the entrance exam, on average (Figure 7), and lower income per capita when entering university (Figure 8). We might assume that those students are either less committed or have had fewer opportunities to learn a second language. More study, however, is still needed in that regard.

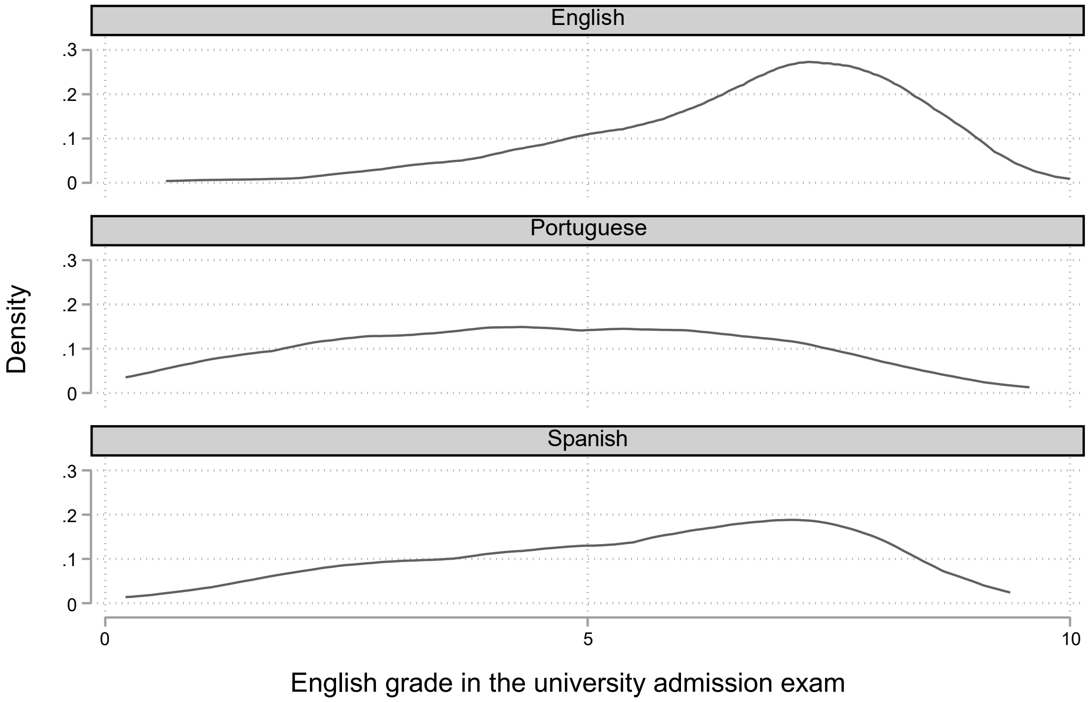

Figure 6 - Distribution of English grades in the university entrance exam by the language of the destination country
Source: Authors' estimation from UNICAMP's microdata.

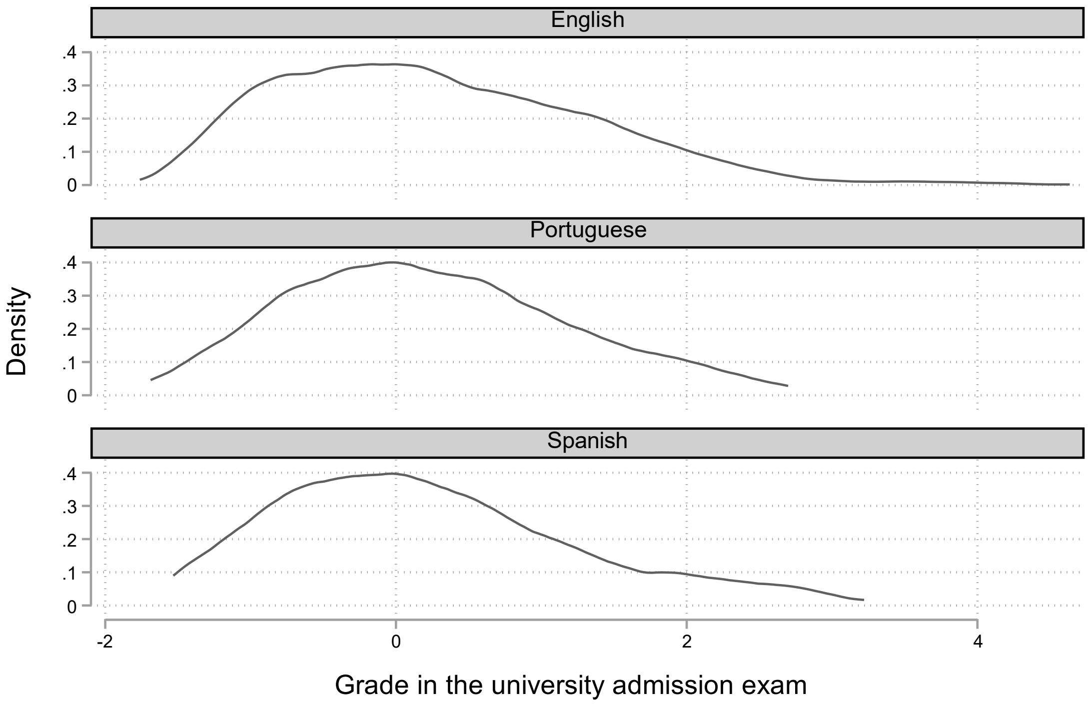

Figure 7 - Distribution of general grades in the university entrance exam by the language of the destination country
Source: Authors' estimation from UNICAMP's microdata.

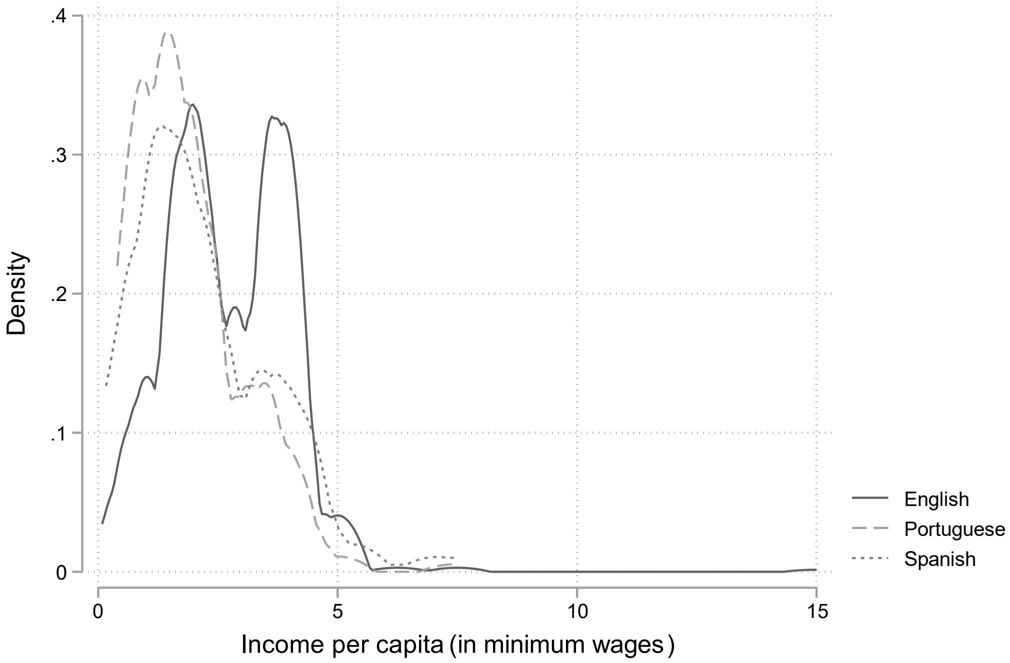

Figure 8 - Distribution of income per capita when entering university by language of destination country
Source: Authors' estimation from UNICAMP's microdata.

5.4. Robustness checks

This section focuses on examining the robustness of the main findings. First, we discuss the internal validity, checking the robustness of our results to the sample selection. Second, we discuss the sensitivity of the results to changing the cutoffs for the heterogeneity analysis.

5.4.1. Subsample results

A possible concern that may arise in our analysis regards the internal validity of the results due to the sample selection, since our sample included both students who completed their courses and those who abandoned university/were dismissed. The latter group was considered in the sample because dropping a course or being dismissed from the university may directly correlate with the student's grades. Since students who graduated may differ from those who did not complete their courses, which could correlate both to treatment assignment and students' final grades, we ran a robustness check considering only the subsample of graduated students. Results are shown in Table 10.

Results from Table 10 shows that our results are indeed robust to the sample selection. Considering the full subsample of students who completed their courses, participation in international student mobility programs do not significantly increase students' overall standardized final grades. However, the temporal dimension still plays a role in changing grades. While negative effects on grades are found for those who traveled at the beginning of university, positive and significant effects are found for students who traveled closer to the end of their courses. We also find that students who participated in mid-term programs are the only group benefiting from mobility (although, for this subsample, the effect of long-term mobility is negative instead of insignificant). Therefore, our main conclusions regarding the temporal dimension still hold.

5.4.2. Changing cutoffs

Another concern that may arise in our analysis is the sensitivity of our results to the choice of cutoffs for the heterogeneity analysis, especially regarding the timing factor (i.e., period elapsed between the starting year at university and the year of the first mobility). To check robustness to different cutoffs, we recalculated the average treatment effect on the treated for different specifications. In the first specification, we grouped together the students who moved after 1 or 2 years after starting university, while the students who travelled in the remaining years (3, 4 and 5) were grouped as a second category. In the second specification, students moving after 1, 2 and 3 years were grouped together, while students going abroad during their 4th and 5th year were considered as a separate group. Lastly, we calculated the impact for all years individually. All results are shown in Table 11.

Results show that changing the cutoffs do not affect our main conclusions. Overall, students traveling at a later stage of their courses benefit more from mobility, while those traveling closer to the beginning of their courses benefit less.

Table 10: Average treatment effect on the treated robustness checks: subsample of students who completed their courses

	Overall results			Time of mobility			Duration of mobility		
	(I)	(II)	(III)	Beginning of the course	Middle of the course	End of the course	Short-term	Mid-term	Long-term
Dependent variable: Final grade	-0.000 (0.021)	-0.003 (0.021)	-0.006 (0.020)	-0.054** (0.021)	0.016 (0.022)	0.041* (0.023)	-0.126*** (0.022)	0.078*** (0.021)	-0.039* (0.022)
Untreated	7836	7836	7836	7836	7836	7836	7831	7836	7836
Treated	1912	1912	1912	722	897	293	491	899	522
Included the covariates of the PSM model	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Included control for year of admission at university	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Included control for undergraduate course	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Authors' estimation from UNICAMP's microdata.

Note. Kernel-based propensity score matching difference in differences estimation; standard errors in parentheses; average treatment effect calculated using the DIFF and the PSMATCH2 packages for Stata; only observations on common support are used; propensity score matching calculated using kernel bandwidth of 0.06; column (I) shows the results of the difference in differences estimation without covariates; column (II) shows the results of the difference in differences estimation including all the covariates used to estimate the propensity score (except for grades in the first semester); column (II) shows the results of the difference in differences estimation including all the covariates used to estimate the propensity score (except for grades in the first semester) and also controls for year of admission and course; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

Table 11: Average treatment effect on the treated robustness checks: time elapsed between the starting year at university and year of first mobility

	1 or 2 years	3, 4 or 5 years	1, 2 or 3 years	4 or 5 years	1 year	2 years	3 years	4 years
Dependent variable: Final grade	-0.048** (0.021)	0.039* (0.021)	-0.005 (0.020)	0.067*** (0.022)	-0.344*** (0.022)	-0.018 (0.020)	0.032 (0.021)	0.095*** (0.022)
Untreated	9489	9489	9489	9489	9473	9489	9489	9489
Treated	742	1198	1638	302	67	675	896	279

Note. Kernel-based propensity score matching difference in differences estimation; standard errors in parentheses; average treatment effect calculated using the DIFF and the PSMATCH2 packages for Stata; only observations on common support are used; propensity score matching calculated using kernel bandwidth of 0.06; the model includes all the covariates used to estimate the propensity score (except for grades in the first semester) and also controls for year of admission and course. Results for five years were omitted due to the small number of observations (only 23 treated units). *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

6. Conclusions

In this paper, we evaluate the impact of international student mobility programs on academic performance (measured by students' grades), focusing on the temporal dimension of those programs. We address two main sub-questions: 1) Does the impact of student mobility on student performance vary across students traveling in different periods of their undergraduate courses? (i.e., is there a best moment to participate in student mobility?); and 2) Does the impact of student mobility on student performance vary across programs with different durations? (i.e., is there a best duration of a student mobility experience?). To the best of our knowledge, this is the first paper to address the temporal dimension of the impact of student mobility on undergraduate students' academic performance. It is also the first focusing on Brazil.

To address these research questions, we use microdata shared directly by the University of Campinas, one of Brazil's most internationalized universities. The average treatment effects on the treated are calculated using Propensity Score Matching (PSM) combined with Difference in Differences (DiD) to minimize the selection problem.

Our results suggest that both the time of mobility and duration matter when it comes to student performance. While negative effects on grades are found for those students who traveled at the beginning of university, positive and significant effects are found for students who traveled closer to the end of their courses. Regarding duration, we found that the period of mobility also plays an important role in academic performance. On average, while student mobility positively impacts students who participated in programs lasting from one semester to one year, negative effects are associated with shorter periods abroad.

Overall, our analysis presents empirical evidence that can be used to design international student mobility programs, providing insights to policymakers engaged in maximizing the effects of their programs. For example, focusing on one-year programs and targeting students after their third year of university may be good strategies to enhance academic performance.

Our results also suggests that, while there seem to be no differences between students coming from different economic and demographic settings, there are differences between students by destination countries. However, additional research is still needed in that regard.

This study is not exempt from limitations. Regarding the strategy used, the matching between treated and not treated students can only be performed based on observed characteristics, requiring the strong assumption that there were no unobserved differences in the treatment and comparison groups also associated with the outcomes of interest. We minimize this kind of bias by adding different covariates in estimating the propensity score and in the final model. The long time span available, together with the detailed information shared by UNICAMP's administration, allowed for a robust matching. Additionally, we also combined PSM with DiD to account for unobserved characteristics that were constant over time.

Additionally, due to data constraints, it is not possible to analytically test the mechanisms behind the results of the heterogeneity analysis, in particular the findings on the temporal dimension and destination region/language. As a future research agenda, we believe that understanding the processes behind the heterogeneity of results is a key for providing improved recommendations for program design. For that, it would be valuable to have more detailed data on a) students' motivations for participating in an exchange program and for the choice of the destination university; b) activities carried out abroad (including the list of courses taken at the host university and the received grades); c) academic challenges that the students faced both during and after traveling; and d) language proficiency in languages other than English immediately prior to traveling.

Finally, in this paper, we focus only on academic performance. Even though we believe that student academic performance is a valuable indicator of human capital, other essential individual, institutional and national outcomes should be considered when designing an academic mobility program. Those factors include but are not limited to student employability, university improvement, and national development. More research is needed to capture the effects of student mobility on those dimensions, both in the short and long run.

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