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International Student Mobility and Academic Performance: Does Timing Matter?

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Abstract
We examine the impact of credit mobility 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 from 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, while negative effects are found for those who travel at the beginning of their university program. Results also show that, while student mobility impacts positively and significantly students who participate in programs lasting from one semester to 1 year, negative effects are associated with shorter periods abroad. Our findings also reveal heterogeneity across destination countries. Mobility has a positive impact on students' grades for those students traveling to English-speaking countries. Our analysis presents empirical evidence that can be used to design international student mobility programs, providing insights to policymakers engaged in maximizing their effects.

Keywords Tertiary education · Grades · Student achievement · Human capital

JEL Classification I23 · I26 · J24

Introduction

A growing number of students are experiencing stay-abroad periods during their tertiary education. Credit mobility is defined as a short-term mobility experience of up to one academic year in a foreign country for study or for an internship, during which a student gains

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credits that will be recognized upon their return to the home country to complete their degree (Junor & Usher, 2008; Teichler et al., 2011).[1] Student mobility is one of the components of transnational higher education with the most significant socio-economic, cultural, and political implications (Guruz, 2008).

Although government support for student mobility programs is not a recent phenomenon, incentives for mobility have expanded in recent years in terms of resources and people involved, and territories covered (Engberg et al., 2014; Guruz, 2008). For example, the total budget for the Erasmus + program, the largest and most reputed European credit mobility program, nearly doubled its financial resources from 2014–2020 to 2021–2027, with a total estimated investment of 26.2 billion euros for the latest period (European Commission, 2021). The program started in 1987 with only 3244 students and now involves more than 300,000 students yearly (European Commission, 2019). Temporal mobility experiences 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 temporal mobility experiences benefit students. For instance, it has been shown that going abroad boosts student's soft skills (Meya & Suntheim, 2014; European Commission, 2016), reputation (Engberg et al., 2014), career prospects (Di Pietro, 2013; Parey & 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 & Suntheim, 2014). However, despite the amount of work on the general impacts, little attention has been dedicated to exploring heterogeneity across mobility programs (Van Mol et al., 2021). For this reason, our work focuses on one of the dimensions differentiating international credit mobility programs, the temporal one.

Students can experience mobility in different moments of their academic careers and stay abroad for short or 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?; (ii) does the impact of student mobility on student performance vary across programs with different durations?

To answer those questions, we use unique data on more than ten thousand undergraduate students who graduated between 2010 and 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 (Contu et al., 2020; Czarnitzki et al., 2021; Di Pietro, 2013; European Commission, 2016; Gonzalez-Baixauli et al., 2018; Meya & Suntheim, 2014; Parey & 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).

[1] It differs from degree mobility for which the student aims to acquire the whole qualification in the foreign country (Teichler et al., 2011).

Brazil also constitutes a very suitable research context due to the process that the country has been experiencing recently. After a period of growth in the mobility phenomena, Brazil is experiencing a trend shift. Between 2000 and 2017, the population of Brazilian students studying abroad increased by 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 (Manços, 2017; Granja & Carneiro, 2020). More recently, however, the growing trend slowed down. The change in 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 the Brazilian federal government's 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. 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 outcomes depending on the type of mobility experience.

Recently, Van Mol et al. (2021) have recognized the importance of analyzing differences across mobility experiences. They distinguished between study levels when going abroad (Bachelor versus Master), the scope of the experience (study versus internship), and the destination country. Differently from them, we focus our attention on programs offering students the opportunity to go abroad at different moments during their studies and choose how long to stay. Moreover, while Van Mol et al. (2021) consider the impact of mobility on labor market returns, we look at the performance of the students when completing their studies upon return. The temporal parameters (time and duration of mobility) are variables that funding agencies and governments can adjust when designing or updating study programs.

This paper is structured as follows. First, it reviews previous studies about the impact of an exchange program on students. 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.

International Student Mobility and Students' Outcomes

Literature has extensively discussed the impact for students of participating in mobility programs during their studies (Roy et al., 2019). 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.[2]

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. Along the same line, a study by the European Commission (2016) about the impact of the Erasmus program on students' personalities, skills, and careers found that an international mobility experience generated positive changes in students' personalities, influencing characteristics considered valuable to employers.[3] According to the study, "the average change achieved in six months through the Erasmus program can be considered equivalent to a personality change that would normally happen over 4 years of life without Erasmus experience" (European Commission, 2016, p. 16).

Studying abroad also has a reputation effect on students. For instance, Engberg et al. (2014)[4] pointed out that receiving a mobility scholarship is already an advantage in itself. They argued that the award is usually seen as a proxy for academic excellence, which guarantees benefits in the labor market for those who obtained it. In addition, receiving high-quality training abroad and developing relationship networks could positively impact 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 3 years after graduation increased by about 22.9% points due to studying abroad. The effect was mainly driven by students from disadvantaged backgrounds (those with one or both parents with lower or upper secondary education). Amendola and Restaino (2017) explored data from a web survey on a cohort of students from the University of Salerno in the South of Italy who participated in the Erasmus program and found that students are generally motivated to go abroad because they believe in benefiting from a boost in their employability, with 61.87% of the surveyed students revealing that prospective employers perceived the mobility experience very positively during job interviews. Bryla (2015) leveraged a large-scale survey among Polish students who participated in mobility programs, finding that one-third attributed a very important role to the mobility experience in their professional

[2] In this section, we exclude studies on degree mobility because the findings of those studies are not directly transferable to our study.

[3] The study 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.

[4] In this section, this is the only cited work that also includes degree mobility. It considers 11 country-case studies of scholarships awarded to attend partial or full study programs.

career development over 5–6 years after their return. Moreover, the author found an association between mobility experiences and some characteristics of the employers. For instance, mobile students are more likely to be employed in companies with a higher level of internationalization. Also, in the same Polish context, Gajderowicz et al. (2012) found that employers perceive mobility as a signal of adaptiveness, motivation, and good learning skills. Employers prefer mobile students, and students who experienced a period abroad during their studies record a higher probability of finding a job and shorter search times than students who pursued their entire studies in Poland. Kratz and Netz (2018) found that facilitated access to job opportunities allows mobile students to obtain higher wage growth through employer changes. Additionally, the higher probability of working in large and multinational firms assures mobile students higher medium-term wages (Kratz & Netz, 2018). Waibel et al. (2018) explored heterogeneities among groups of individuals experiencing mobility. They found that those who benefited the most from mobility were those with the lowest propensity to study abroad, i.e., those from disadvantaged economic, social, and cultural groups. The positive effect of student mobility on early career occupational status is limited to graduates from generalist fields of study, while graduates from specialized fields have smooth access to the job market, regardless of their experiences in foreign countries. Netz and Grüttner (2020), when analyzing if the effect of studying abroad on graduates' labor income varies across social groups in the German labor market, found that graduates from a high social origin benefit slightly more from international student mobility than those coming from a low social origin, concluding that student mobility tends to foster the reproduction of social inequalities in the labor market. In turn, Parey and Waldinger (2011) 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% 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. However, not all studies converge in finding positive returns to mobility concerning students' careers. For instance, Van Mol et al. (2021), having controlled for selectivity into student mobility, found that mobility does not impact early career outcomes, either in terms of wages or the time to find a job after graduation.

One way studying abroad can impact employability is by acquiring 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, the latter being the languages 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.

The closest branch of studies to ours investigates how participating in an international study program affects 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. However, the grade increase was mainly driven by the mere transfer of grades obtained abroad. 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 positively impacted the graduation bonus of students, focusing 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 concerning their academic performance. 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% in their final grade compared to non-mobile students. That effect was heterogeneous regarding the field of study, type of exchange, and the 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, 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 credit 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 (such as timing and duration), parameters that policymakers can adjust to increase the efficiency of those programs. Even though the academic literature already acknowledges the temporal dimension of exchange programs,[5] to the best of our knowledge, no studies asked whether there is a more appropriate moment or duration of a student mobility experience to increase students' performance.

Data

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 (Times Higher Education, 2020). The university is located in São Paulo state, the Brazilian state with the highest Gross Domestic Product in the country (Brasil, 2020b).

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

The choice for UNICAMP is because the university has broad experience with internationalization initiatives such as international cooperation and student mobility. Since its foundation in the 1960s, internationalization has been part of its primary institution strategy (Granja & Carneiro, 2020). The university is highly involved in the population of mobility programs in the country. For example, in the case of the Science without Borders program, UNICAMP placed itself in seventh place among the top 10 universities in terms of the number of students sent abroad (Brasil, 2016). Most universities ranked in this top 10 were large research-intensive public universities with similar characteristics to UNICAMP in terms of size and type (Schwartzman et al., 2021).[6]

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 similar, programs have different natures and settings. For example, 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.

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 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, usually lasting between one semester and 2 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, 1943 participated (at least once) in an institutional student mobility program (17% of the entire sample), while 9489 were in the non-treated (nonparticipants) group.[7]

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 from 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

[6] In addition to UNICAMP, the other universities in the top 10 were the following: University of São Paulo, Federal University of Minas Gerais, Federal University of Rio de Janeiro, University of Brasília, Federal University of Santa Catarina, São Paulo State University Júlio de Mesquita Filho, Federal University of Rio Grande do Sul, Federal University of Pernambuco and Federal University of Ceará.

[7] The dataset structure did not allow us to capture students who traveled 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.

course load (credits). The resulting aggregated grade is called Performance Coefficient. 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 helps 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.[8]

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 (for instance, due to low grades or low progression). For students who met 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, so excluding them might determine a selection problem. As a robustness check, we also 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 were not considered, as we aim to evaluate the impact of mobility on the overall student's career, and those students do not have a final semester grade. Moreover, for the students who have not completed their study path, it is impossible to determine either the amount of time spent abroad or the participation in a mobility program if they go abroad later in their studies.

To ensure that each student was considered only once in the sample, only students registered for only one undergraduate course (who 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 the university through the regular selection process (through an entrance exam) were considered.[9]

Figure 1 shows the distribution of the grades for the last semester at the university for mobility students (also referred to from now on as the treatment group) and non-mobility students (non-treated or nonparticipants group). As we can observe, students who participated in international mobility programs had slightly higher final grades than the nonparticipants.[10] However, those differences cannot yet be attributed only to participation in mobility programs.

[8] 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. The formula used by UNICAMP is equivalent to calculating the Z-score of the PC. 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 (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.

[9] 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).

[10] Difference between participants and nonparticipants of mobility programs is statistically significant at the 1% level (|t-value|= 8.400, p-value = 0.0000).

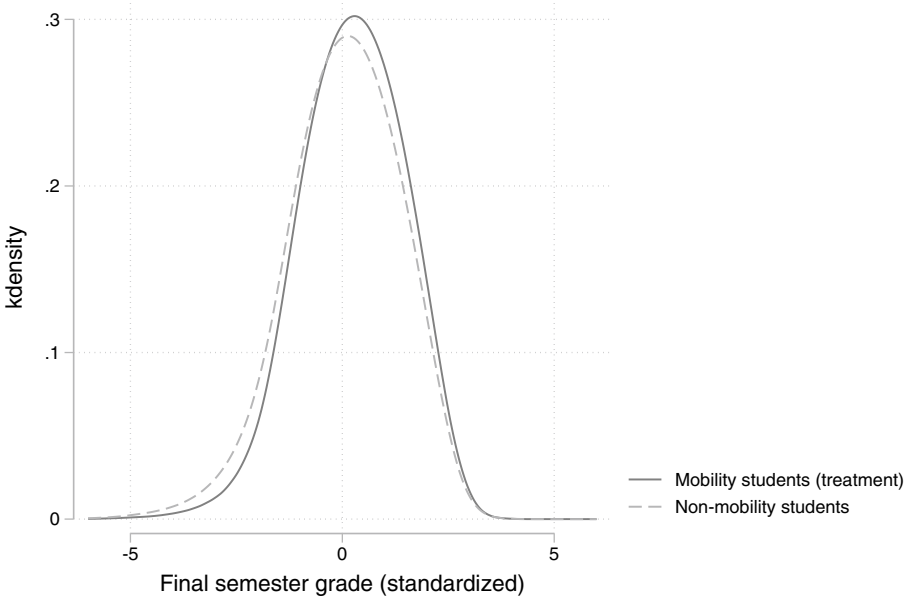

Fig. 1 Dependent variable kernel density (mobility vs. non-mobility students). *Data source* Authors' estimation from UNICAMP's microdata

Table 1 lists and describes all the variables included in our analysis. The rationale for choosing the independent variables is explained in detail when discussing the empirical strategy. Students' academic, demographic, and socio-economic information was shared directly by the UNICAMP's Academic Board and International Office after the approval of the Brazilian Research Ethics Committee.[11]

Table 2 shows the summary statistics for our sample of students. Not surprisingly, treated and non-treated 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 50th 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 mobile students and 49% of non-mobile 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 1 year younger than nonparticipants when entering university. Those figures suggest self-selection in the sample, meaning that participants and nonparticipants in mobility programs would differ even without treatment (Caliendo & Kopeinig, 2008). The self-selection challenge is well-known in the study abroad literature (Kim & Lawrence, 2021; Meya & Suntheim, 2014) and will be discussed in the next section.

[11] Protocol number 25285919.6.0000.8142.

Table 1 Variables description

Variable	Measure
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
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 (top 50th percentile) and 0 otherwise[a]
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 1 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)

[a]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)

Empirical Strategy

To reduce the possible bias due to the selection of mobility programs, the methodology chosen for the analysis is a combination of Propensity Score Matching (PSM) and Difference in Differences (DiD). The sections below explain how both techniques were used in this study.

Searching for a Group of Potential Applicants

The final control group for our analysis was selected using Propensity Score Matching within the sample of all non-mobile students. 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 non-treated units (Gertler et al., 2016). It works by comparing treated and non-treated units with a similar probability

Table 2 Summary statistics of participants and nonparticipants

	Total			(1) Participants (Mobility students)			(2) Nonparticipants			t-value (1) vs. (2)
	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD	
Grade last semester (standardized)	9340	0.076	0.881	1749	0.235	0.759	7591	0.04	0.903	8.400***
Grade first semester (standardized)	11,432	0.104	0.886	1943	0.504	0.699	9489	0.022	0.898	22.280***
Student's pre-university academic ability (standardized grade in the entrance exam)	11,432	0.013	0.983	1943	0.288	1.029	9489	− 0.043	0.964	13.630***
Income per capita of household before entering university (if top 50th percentile)	11,432	0.469	0.499	1943	0.552	0.497	9489	0.451	0.498	8.090***
Education of the parents (if parents had access to tertiary education)	11,432	0.62	0.485	1943	0.706	0.456	9489	0.603	0.489	8.590***
Gender (if female)	11,432	0.487	0.5	1943	0.461	0.499	9489	0.492	0.5	− 2.520**
Race/Skin color (if black, brown or indigenous)	11,432	0.137	0.344	1943	0.108	0.311	9489	0.143	0.35	− 4.040***
Age when entering university	11,432	19.951	3.141	1943	19.127	1.372	9489	20.12	3.366	− 12.780***
Previous internal mobility experience	11,432	0.133	0.34	1943	0.172	0.378	9489	0.125	0.331	5.620***
Year eligible for the SwB program (if yes)	11,432	0.901	0.299	1943	0.976	0.152	9489	0.885	0.318	12.290***
Area eligible for the SwB program (if yes)	11,432	0.668	0.471	1943	0.76	0.427	9489	0.649	0.477	9.480***

Data source Authors' estimation from UNICAMP's microdata

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

(propensity score) of receiving a specific treatment (Caliendo & Kopeinig, 2008; Gertler et al., 2016). As stated by Netz and Grüttner (2020), PSM has become a very popular technique in the international student mobility literature for several reasons. One reason is that, unlike many regression techniques, it forces researchers to reflect upon the process of selection into international mobility by identifying the factors increasing the probability of experiencing mobility. A second reason is that it has the advantage of only comparing very similar treated and not treated individuals. Third, by presenting a non-parametric method of causal inference, it makes no assumptions about how variables are distributed and what the functional form of their relationships is.

To identify potential mobile students within the group of non-mobile students, we considered as relevant matching characteristics the following: students' 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 academic performance.

As family 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' socio-economic background since students from higher-income families may be more likely to pursue part of their studies abroad (European Commission, 2016; Junor & Usher, 2008; Meya & 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 et al., 2001). Parents' education was also added to account for social capital, as highly educated parents might support an exchange financially and by highlighting the benefits of learning about other countries, languages, and cultures (Di Pietro, 2019; Meya & 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 move to another country and spend more effort finding the perfect match regarding university and field of study (Meya & Suntheim, 2014).

As students' academic performance, we added the grades in the first semester of university 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 & 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 (such as 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.

Table 3 Participation in student mobility programs (probit results)

Dependent variable: Pr(Student Mobility = 1)	Coefficients		Marginal Effects	
	Coef	SE	Coef	SE
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	11,432			
Pseudo R^2	0.110			
χ^2	840.470			
Prob > χ^2	0.000			

Data source Authors' estimation from UNICAMP's microdata

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

We predict the propensity score using a binary Probit linear probability model[12] and report the results in Table 3. In the model, the dependent variable is a binary that takes the value of 1 if the student participated in an institutional mobility program in the period between 2010 and 2020 and 0 otherwise. As independent variables, we consider: grade in the first semester; student's pre-university academic ability; income per capita of household before entering university; education of the parents; gender; race/skin color; age when entering university; previous internal mobility experience; year eligible for the SwB program; area eligible for the SwB program.

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.

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 of checking the balance 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^2 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 non-treated group) and Rubin's R (the ratio of treated to non-treated 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.

While propensity score matching can be a powerful tool, it relies on several assumptions to produce reliable results. The two main assumptions are discussed below.

Propensity Score Matching Assumptions

Conditional Independence (CI)

The Conditional Independence assumption (also called unconfoundedness or selection on observables) states that differences in outcomes between treated and comparison individuals with the same values for pre-treatment covariates are attributable to treatment (Caliendo & Kopeinig, 2008). The main challenge with the CI is that it is a very strong assumption

[12] A possible concern that may arise in our analysis regards the choice of the binary model (probit instead of logit). As observed by Caliendo and Kopeinig (2008, p.37): "*For the binary treatment case, where we estimate the probability of participation versus nonparticipation, logit and probit models usually yield similar results.*" Indeed, we tested logit versus probit in our sample and observed that both models resulted in the same conclusions. The results of the logit model are available upon request.

Table 4 Balancing results before and after matching

Variable	Sample	Mean		Bias (%)	t-test	
		Treated	Control		t	p>t
Grade first semester (standardized)	Unmatched	0.50378	0.02244	59.8	22.28	0.000
	Matched	0.5006	0.42887	8.9	2.87	0.004
Student's pre-university academic ability (standardized grade in the entrance exam)	Unmatched	0.2882	− 0.04293	33.2	13.63	0.000
	Matched	0.2829	0.21619	6.7	1.87	0.062
Income per capita of household before entering university (if top 50th percentile)	Unmatched	0.55172	0.45147	20.1	8.09	0.000
	Matched	0.55155	0.53049	4.2	1.22	0.223
Education of the parents (if parents had access to tertiary education)	Unmatched	0.70612	0.60259	21.9	8.59	0.000
	Matched	0.70619	0.68727	4.0	1.19	0.235
Gender (if female)	Unmatched	0.46063	0.49204	− 6.3	− 2.52	0.012
	Matched	0.46134	0.48597	− 4.9	− 1.42	0.155
Race/Skin color (if black, brown or indigenous)	Unmatched	0.10808	0.14259	− 10.4	− 4.04	0.000
	Matched	0.10825	0.1129	− 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	0.17241	0.12499	13.4	5.62	0.000
	Matched	0.17165	0.15666	4.2	1.16	0.245
Year eligible for the SwB program (if yes)	Unmatched	0.97633	0.88545	36.4	12.29	0.000
	Matched	0.97629	0.96758	3.5	1.54	0.125
Area eligible for the SwB program (if yes)	Unmatched	0.75965	0.64886	24.5	9.48	0.000
	Matched	0.75928	0.72981	6.5	1.95	0.051

Table 4 (continued)

Sample	Pseudo R^2	LR χ^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

Data source Authors' estimation from UNICAMP's microdata

*If B > 25%, R outside [0,5; 2]

and 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 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 (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 looked for other possible 'hidden' criteria that may have affected both participation and the outcome of interest by adding socio-economic 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 student's 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 socio-economic status). Finally, 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.

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 non-treated 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 (D) (Heckman et al., 1999). The assumption can be written as follows:

$$0 < P(D = 1|X) < 1$$

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 & Kopeinig, 2008). Figure 2 shows the distribution of the propensity scores for both the treatment and control groups in the sample. As expected, control units had their distribution of propensity scores more skewed to the right compared

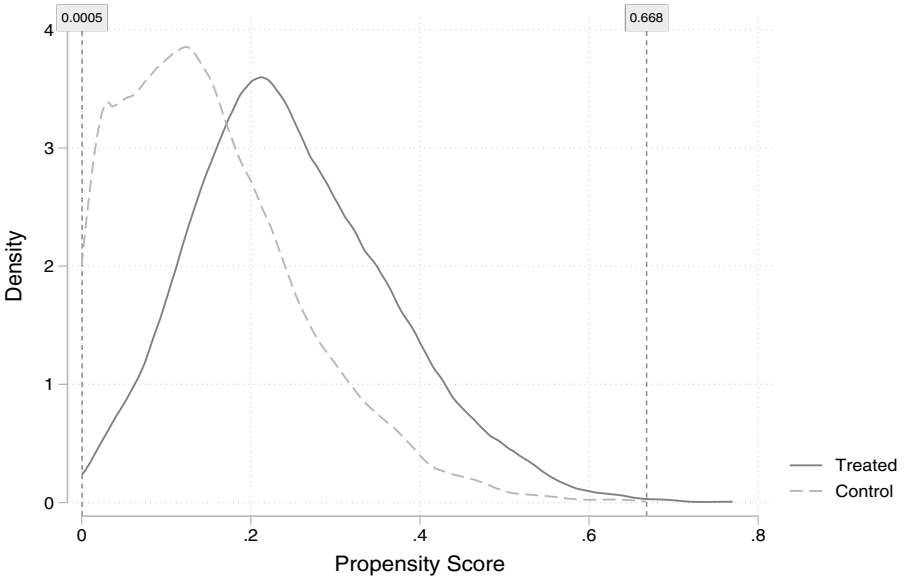

Fig. 2 Distribution of the propensity scores for treatment and control groups (Common Support Assumption). *Data source* Authors' estimation from UNICAMP's microdata

to the treated units. The graph shows that the common support assumption was satisfied, with 99.8% treated observations within the common support area.

Difference in Differences Estimation

Since baseline data on our outcome of interest (student performance) was available, we decided to combine the matching with a Difference in Differences estimation, a method that compares the changes in outcomes over time between treated and non-treated units (Gertler et al., 2016). The advantage of combining both methodologies is to reduce bias since the combination controls for observable differences between groups and solves the issue of any unobserved characteristic constant across time between both groups (Caliendo & Kopeinig, 2008; Gertler et al., 2016). This combination is useful as selecting a control group using PSM can only tackle observed selection into international student mobility, not dealing with selection bias occurring from unobserved heterogeneity between individuals going abroad and staying at home (Netz & Grüttner, 2020).

We explore the impact of student mobility programs on student academic performance as measured by the average treatment effect on the treated (ATT) students (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:

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

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

Our model is given by:

Table 5 Average treatment effect on the treated

	(I)	(II)	(III)
Dependent variable: final grade	0.010	0.012	0.006
	(0.021)	(0.020)	(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

Data source Authors' estimation from UNICAMP's microdata

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 (III) 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

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

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 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 model and represents the average treatment effect in a Difference in Difference estimation.

To combine DiD with PSM, the regression used weights derived from the propensity score,[13] and considered only the region of common support, i.e., where there is overlap in the propensity score distribution for both treated and non-treated students.

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 for this analysis is mainly because doing an experimental framework (such as a Randomized Control Trial), where students are randomly assigned to study abroad (as in a lottery), was not feasible in our 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. In fact, UNICAMP has several different mobility programs, and students are not restricted to only applying to one of them.

[13] In this study, we use Kernel Propensity Score Matching. Kernel matching is a non-parametric matching estimator which uses weighted averages of all individuals in the control group to construct the counterfactual outcome. The weights used depend on the distance between each individual from the control group and the participant's observation for which the counterfactual is estimated. Kernel matching has the advantage of lowering the variance, which is achieved because more information is used (Caliendo & Kopeinig, 2005).

Results and Discussion

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 stated in "International Student Mobility And Students' Outcomes" section, 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 regarding the impact on grades. Researchers on this topic agree that the impact of a mobility program on students is context-specific and varies across mobility programs and students' characteristics.

For that reason, in the next subsections, we investigate the possible heterogeneous impacts of student mobility programs on 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?; (2) does the impact vary across programs with different durations? Additionally, we also investigate possible economic and demographic heterogeneous effects and effects related to the destination region.

Does the Impact of Student Mobility on Student Performance Vary Across Students Traveling in Different Periods of Their Undergraduate Program?

To answer the first question, we disaggregate the effects of student mobility by 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 an 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. Considering that just a few students traveled between the first and the second year (only 3%), those who attended university for one or 2 years before mobility were considered 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 3 years after starting university).

Looking at the distribution of the students in our sample by the number of years before the first international mobility, most students at UNICAMP can be considered as Type II (46%), while 38% are Type I and 16% Type III.

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

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

Data source Authors' estimation from UNICAMP's microdata

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

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).[14] Those results suggest that the time of mobility matters when it comes to increasing final grades.

At UNICAMP, most of 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 due to different grading systems at the host institutions. With that in mind, a possible explanation for our results can be found in students' behavior. Students in their first university years 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: adapting to university and a different country.

Moreover, traveling before being wholly integrated into their home universities may impose difficulties in re-entering the home education system when returning, impacting exam performance. 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. Currently, UNICAMP's data does not allow testing of these mechanisms, and further research should address those aspects.

While the choice of the cutoffs for distinguishing the three types of students was based on the structure of undergraduate courses in Brazil, in "Changing cutoffs" section we report a sensitivity analysis of our results to our cutoff choice.

[14] As final grades in our model are measured as the Z-score of a student's performance coefficient, it captures how many standard deviations a data point is away from the mean of a distribution. In our case, a decrease of 0.05 in the final grades means that the data point has moved 0.05 standard deviations further away from the mean of the student's class as a result of participating in a student mobility experience.

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: Final grade	− 0.099***	0.082***	− 0.024
	(0.022)	(0.021)	(0.021)
Untreated	9488	9489	9489
Treated	497	912	531

Data source Authors' estimation from UNICAMP's microdata

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

Does the Impact of Student Mobility on Student Performance Vary Across Programs with Different Durations?

To answer the second question, we disaggregated the effects by 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 1 year);
- Type C: students who experienced long-term mobility (more than 1 year).

In our sample, 26% experienced short-term mobility, 27% stayed abroad for more than 1 year, while the remaining 47% experienced mid-term mobility.

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 1 year, negative effects were associated with shorter periods abroad. That suggests that mobility duration 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.

Those results may be explained by the fact that short-period stays can distract students since adapting to a new country and a different higher education system usually takes some

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

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	0.005	0.018	0.004	− 0.052	0.027	− 0.045	0.041
	(0.029)	(0.027)	(0.057)	(0.021)	(0.033)	(0.025)	(0.027)	(0.029)
Untreated	4669	4820	1353	8136	3771	5718	5205	4284
Treated	895	1045	210	1730	570	1370	870	1070

Data source Authors' estimation from UNICAMP's microdata

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

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	− 0.008	− 0.016	0.116***	0.138***	0.107***	− 0.153***	0.032
	(0.021)	(0.020)	(0.022)	(0.021)	(0.021)	(0.021)	(0.022)	(0.021)
Untreated	9489	9440	9479	9488	9477	9489	9471	9488
Treated	974	42	51	334	180	752	170	138

Data source Authors' estimation from UNICAMP's microdata

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

time. Therefore, spending more time abroad gives students more chances to re-evaluate their relationship with their courses.

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 1 year). The fact that long-term programs do not positively impact students' grades could be related to the fact that students may face challenges in readjusting to their home universities after spending a long time abroad. However, additional research is still needed to test those hypotheses empirically.

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).[16]

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. A positive impact on grades was found for students traveling to North America (the 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 (i.e., with the same language spoken in Brazil).

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

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 canceled in the following years, when it became clear to policymakers that students were choosing Portugal due to its language. That is because applying for an exchange program to go to Portugal usually does not require knowledge of another language other than Portuguese. 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 (Fig. 3).[17] They also had slightly lower grades in the entrance exam, on average (Fig. 4), and lower income per capita when entering university (Fig. 5). We might assume that those students are either less committed or have had fewer opportunities to learn a second language. On the other hand, studying in English might result from strategic thinking, a willingness to invest extra effort, and an ambition to have a prestigious institution mentioned in the curricula. Further investigation, however, is still needed in that regard.

Robustness Checks

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 the 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 show that our results are overall robust to the sample selection. Considering the full subsample of students who completed their courses, participation in international student mobility programs does not significantly increase students' overall standardized

[17] The authors chose not to include the grades in the English exam at the university entry as a control in our original model because UNICAMP's mobility programs do not target exclusively English-speaking countries. For instance, Portuguese universities do not require a language other than Portuguese, the official language in Brazil. Other countries typically require proof of language proficiency, but UNICAMP does not record the results of those language tests. The English tests recorded by the university are those part of the university selection exam and not the official English proficiency tests used to select mobility students (e.g., TOEFL or IELTS). Moreover, having high grades in English does not necessarily guarantee a higher probability of participating in mobility because the student could travel to non-English speaking countries or could improve the English skills in the period between entering university and applying for mobility.

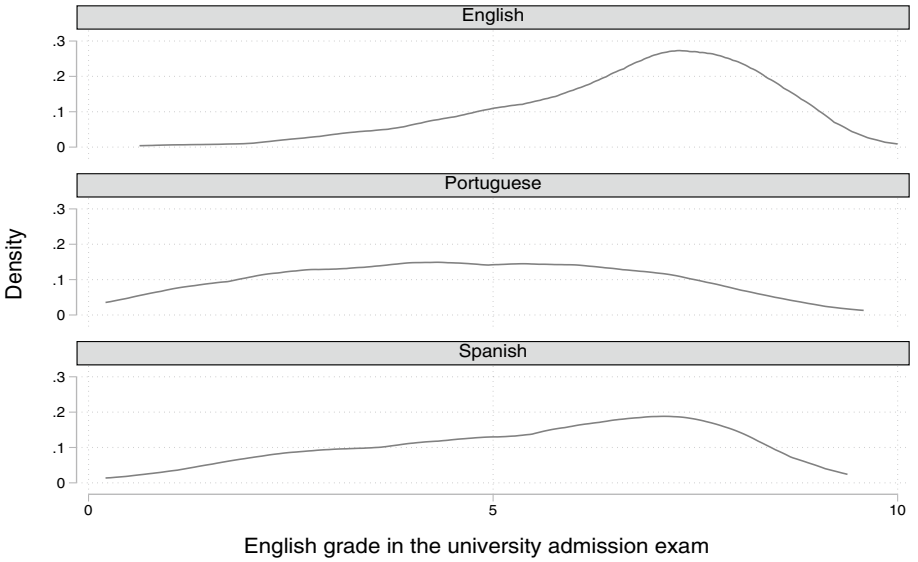

Fig. 3 Distribution of English grades in the university entrance exam by the language of the destination country. *Data source* Authors' estimation from UNICAMP's microdata

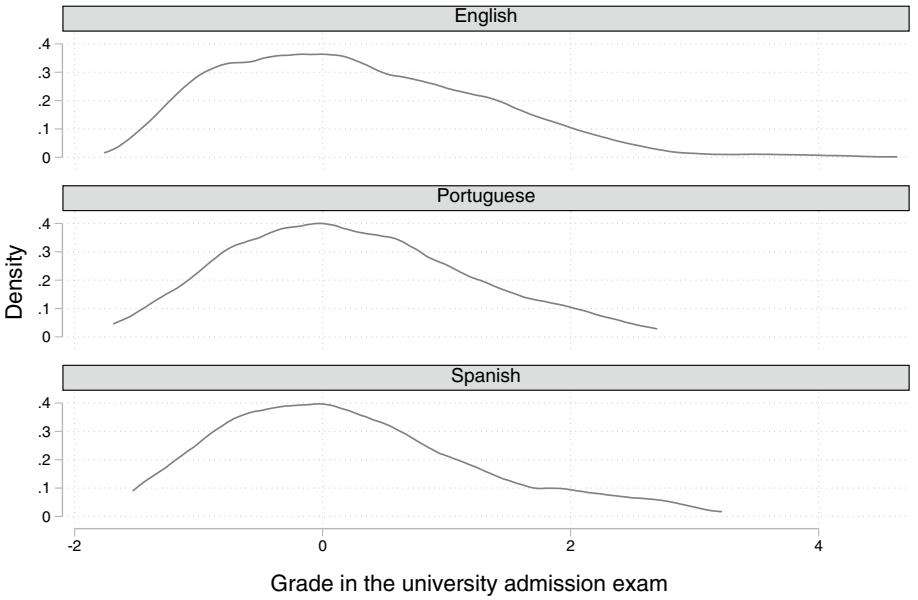

Fig. 4 Distribution of general grades in the university entrance exam by the language of the destination country. *Data source* Authors' estimation from UNICAMP's microdata

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,

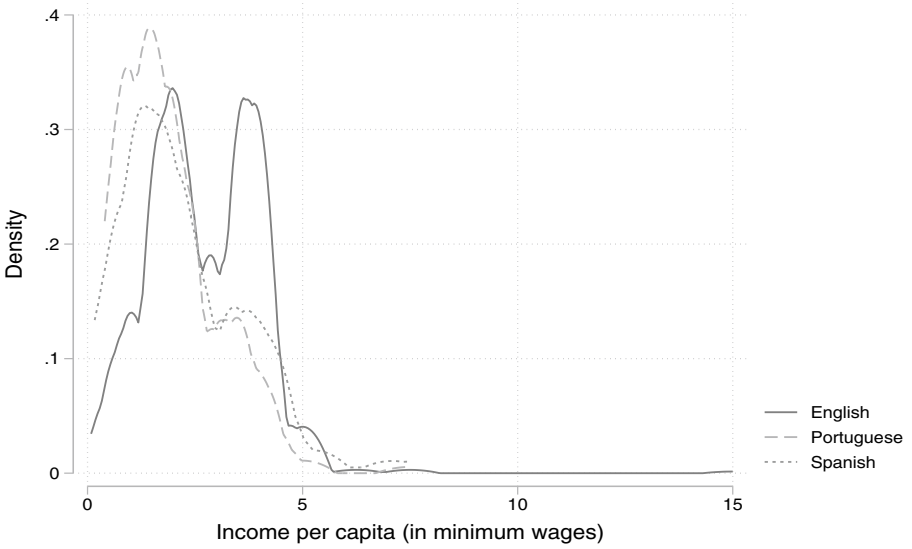

Fig. 5 Distribution of income per capita when entering university by the language of the destination country. *Data source* Authors' estimation from UNICAMP's microdata

positive and significant effects are found for students who traveled closer to the end of their courses.

We also find that the only students who benefit from mobility are those who experience mid-term mobility. Short-term mobility, as well as long-term mobility, are detrimental to students. Therefore, our main conclusions regarding the temporal dimension of mobility are consistent with the main findings reported previously in "Impact of mobility programs on academic performance" section. The only difference is that the negative sign of long-term mobility turns significant in the subsample of students who completed their courses, while it is insignificant in the original model.

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 (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 those who traveled 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. Results from our estimation showed that changing the cutoffs did not affect our main conclusions. Overall, students traveling later in 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	− 0.003	− 0.006	− 0.054**	0.016	0.041*	− 0.126***	0.078***	− 0.039*
	(0.021)	(0.021)	(0.020)	(0.021)	(0.022)	(0.023)	(0.022)	(0.021)	(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

Data source Authors' estimation from UNICAMP's microdata

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 (III) 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

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?; and (2) Does the impact of student mobility on student performance vary across programs with different durations? 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 to focus 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 combined with Difference in Differences to minimize the selection problem.

Our results suggest that both the time of mobility and duration matter for 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 mobility duration 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 1 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 1-year programs and targeting students after their third year of university may be good strategies to enhance academic performance.

Our results also suggest 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 no unobserved differences in the treatment and comparison groups are also associated with the outcomes of interest. We minimized this bias by adding different covariates to estimate the propensity score and the final model. The long time span and the detailed information shared by UNICAMP's administration allowed for a robust matching. Furthermore, we also combined PSM with DiD to account for any unobserved characteristics that were constant over time.

Additionally, due to data constraints, it was 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 key to providing improved recommendations for program design. For that, it would be valuable to have more detailed data on (a) the country and institution where the student traveled to; (b) students' motivations for participating in an exchange program and for the choice of the destination university; (c) activities carried out abroad (including the list of courses taken at the host university and the received grades); (d) academic challenges

that the students faced both during and after traveling; and (e) 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, individual, institutional, and national outcomes should also be considered when designing an academic mobility program. Those factors include but are not limited to student employability, university improvement, and national development. Further research is needed to capture the effects of student mobility on those dimensions, both in the short and long run.

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Author Contributions CDG: Conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing—original draft, writing—review and editing, visualization. FV: Conceptualization, methodology, formal analysis, resources, writing—review and editing, supervision.

Data Availability The paper uses administrative data of former students of the University of Campinas, Brazil, shared after the approval of the Brazilian Research Ethics Committee (Protocol No. 25285919.6.0000.8142). Given that these data contain personal identifiers and sensitive information, we cannot make the data publicly available. Researchers can obtain the data by filling in a request directly with the university's administration. The authors commit to providing guidance about obtaining the data. The authors agree to share the command files used to produce the results upon request.

Declarations

Conflict of interest This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The authors disclose no relevant financial interests related to the research in this paper.

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