Can international mobility shape students' attitudes toward inequality?

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CAN INTERNATIONAL MOBILITY SHAPE STUDENTS' ATTITUDES TOWARD INEQUALITY? THE BRAZILIAN CASE

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ABSTRACT

In this study, we examine the impact of international mobility programs on students' attitudes toward inequality, focusing on two dimensions: preference and perception of inequality. To provide causal evidence, we exploit unique survey data about more than a thousand students from a well-known and internationalized Brazilian university. Using Propensity Score Matching to construct an artificial comparison group, we find that going abroad does not affect students' preference to reduce within-country inequality in Brazil. Still, international mobility affects students' salary preferences, with mobile students expressing their preferences for favoring a raise in salaries for high-skilled jobs. Results also show that mobility affects how individuals perceive current inequality, as students who participate in mobility programs believe within-country inequality is smaller than their non-mobile counterparts. Our analysis presents empirical evidence to reflect on the role of international student mobility, providing insights to policymakers engaged in understanding their effects.

Keywords: Exchange Programs; Income Redistribution; Tertiary Education; Impact Evaluation; Propensity Score Matching

JEL Classification: D31; D63; I24

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1. INTRODUCTION

Student mobility, defined as "any academic mobility which takes place within a student's program of study in post-secondary education" (Junor & Usher, 2008, p. 3), is an activity that, although not new, has been receiving more attention from governments in the past decades (Guruz, 2008; Engberg *et al.*, 2014). Between 2011 and 2018, the world experienced an increase of 40% in mobile students at the tertiary level, reaching an estimated 5.6 million students abroad (UNESCO, 2021).

There are several reasons why nations invest in international student mobility programs. Through the provision of education abroad, those programs can contribute to human capacity development, organization improvement, increase global connections, as well as to reduce social inequalities (Engberg *et al.*, 2014).

The literature on student mobility has underlined the benefits of international mobility for beneficiaries. Previous studies have shown that going abroad can impact students in several dimensions. For example, a mobility experience can improve students' career prospects (Parey & Waldinger, 2011; Di Pietro, 2013), soft skills (European Union, 2016), the acquisition of new skills (Sorrenti, 2017; Wang, Crawford & Liu, 2019), reputation (Engberg *et al.*, 2014), as well as student performance (Meya & Suntheim, 2014; Gonzalez-Baixauli, Montanes-Brunet & Perez-Vazquez, 2018; Contu *et al.*, 2020; Granja & Visentin, 2021).

It has also been shown that mobility is associated with a change in students' personal development and cross-cultural skills. A study on American students by Clarke III *et al.* (2009) shows that mobile students reported that going abroad has made them more proficient, approachable, and open to intercultural communication. Zimmermann and Neyer (2013) find that German exchange students are more open and agreeable and less neurotic than non-mobiles. A study by the European Union (2016) about the impact of the Erasmus program on students' personalities, skills, and careers found that an international mobility experience is associated with a change in students' personalities, influencing characteristics considered valuable in the labor market.

Our study contributes to the literature on international student mobility by focusing on its impact on students' subjective worldviews. We ask: Does participating in exchange programs affect an individual's attitudes toward inequality? To examine the effects on attitudes towards inequality, we consider two dimensions: preference and perception of economic inequality.

To provide causal evidence, we exploit unique data of more than one thousand (former) students from a well-known and internationalized Brazilian university, the University of Campinas. Administrative data shared by the university's Academic Board and International Office was complemented with data collected through an online survey administered in May 2021.

Using Propensity Score Matching to construct an artificial comparison group, we find that going abroad does not affect students' preferences regarding reducing within-country inequality. Still, international mobility affects students' salary preferences, with mobile students expressing a preference for higher salaries for high-skilled jobs. Results also show that mobility affects how individuals perceive current inequality, as those participating in mobility programs believe within-country inequality is smaller than their non-mobile counterparts. Our main results are not sensitive to changing the matching technique or altering how we measure students' preferences.

Even though the literature about the impact of international student mobility is extensive, to the best of our knowledge, this is the first study addressing empirically the effect of going abroad on students' preferences and perception of inequality. Moreover, this is the first paper addressing the impact on students' worldviews conducted in a Latin American country. Despite an increase of 40% in the number of tertiary students studying abroad from 2011 to 2018 (UNESCO, 2021), Latin America and the Caribbean areas are still neglected by studies on international mobility, which usually focus on developed regions, such as North America and Europe.

The peculiarities of Brazil make it an interesting case study to investigate the relationship between mobility and attitudes toward inequalities. First, students' mobility is a relevant phenomenon for the country. Mobility has been promoted by a massive and costly exchange program that has sent more than 90 thousand Brazilians to study abroad, called Science without Borders (Brasil, 2016). In the last decades, the number of Brazilian exchange students has risen drastically: going from 18.5 to 58.9 thousand between 2000 and 2017, growing by more than 200 percent (UNESCO, 2021). However, more recently, the country has experienced a trend shift. Following an economic and political crisis, the Brazilian higher education system suffered severe budget cuts that reduced the resources allocated to international mobility programs (Andrade, 2019; De Negri, 2021). Consequently, it became important to investigate the impact of mobility programs and warn (if needed) about the consequences of cutting them.

Second, inequality is one of the core issues for Brazil. Brazil has recorded a high inequality level for decades, and the situation has been exacerbated due to the recent COVID-19 pandemic. The pandemic has intensified social and economic inequalities in the country, with minorities and low-income individuals being more exposed to the disease and more likely to have worse infection outcomes (Nassif Pires *et al.*, 2021). In addition, the Word Bank has also raised concerns about the post-pandemic recovery (World Bank, 2019). According to its statistics, even though all people experienced losses during the pandemic, the poorest 20 percent were the ones who experienced the most significant drop in income (Gopalakrishnan *et al.*, 2021).

In this context, understanding the factors driving the attitudes towards inequalities of the young generation (especially university students) might help find solutions to improve the country's current conditions. Given that university students tend to be drawn from or to be mobile to the higher echelons, where there is more political influence, understanding the sources and effects on their views about inequality becomes essential. Additionally, since elected officials tend to implement policies that reflect public opinion (Lubker, 2004; Andersen & Yaish, 2012; Kim *et al.*, 2017; OXFAM, 2017; Becker, 2021), understanding how individuals perceive and react to economic inequality becomes crucial. The citizens' perceptions might drive political behavior in favor or against income-redistributing policies.

Our study digs into attitudes towards inequality in Brazil and sets the basis for further research on the effect of international student mobility, providing insights to policymakers engaged in understanding its consequences.

The paper is structured as follows. First, it presents a literature review on attitudes toward inequality. Second, it describes our data and chosen methodology. Third, it illustrates our results, including a set of heterogeneity analyses. Finally, the paper discusses the results and highlights the main conclusions.

2. SUBJECTIVE VIEWS ON INEQUALITY: PREFERENCE AND PERCEPTION

Economic inequality, understood as the income/wealth gap between the richest and poorest segment of the population (Jetten *et al.*, 2021; Casara *et al.*, 2022), has intensified considerably in the last decades, capturing the attention of academics and becoming part of the agenda of many politicians (Becker, 2021; Jetten *et al.*, 2021).

Facing inequality, individuals might have different subjective views, which could be related either to their beliefs about how inequality should be (inequality preferences) or to how they estimate inequality (inequality perceptions).

Inequality Preferences

We understand inequality preferences in this study as the same as beliefs about inequality, which can be defined as "normative ideas about just inequality (i.e., thoughts about what should be)" (Janmaat, 2013, p.359).

When looking at individual preferences, previous studies showed that how people judge inequality depends on several contextual factors, such as sociodemographic characteristics or the social values and ideology embraced.

As sociodemographic factors, extant works have considered the role occupied by the individual in society, economic conditions, level of education, gender, and age. For instance, considering the economic conditions, using data from the World Values Survey and the European Values Study from 102 countries, Medgyesi (2013) observed that people in higher positions in the income distribution tend to accept greater income disparities while manual workers are the group with less acceptance of inequality. In the same line, also using data from the World Values Survey and national-level statistics for 24 OECD countries, Curtis and Andersen (2015) noticed that, in most countries, people with lower levels of income (i.e., belonging to the working class) are more likely to believe that inequality should be reduced. The conclusion that lower-income groups, as well as those occupying occupations that require less training, have more egalitarian preferences when compared with higher-income groups was confirmed by other studies, such as in Guillaud (2013), Andersen and Yaish (2012), Reeves and Mager (2018), Roex *et al.* (2018), Ohtake (2008), and Jaime-Castillo and Saez-Lozano (2016).

In addition to objective economic status, subjective factors may also influence people's preferences for inequality. Guillaud (2013) found, for instance, that people who express the feeling of belonging to the upper class are less inclined to favor redistribution than those who place themselves in the middle class. The author also found that those who reported downward mobility in the past ten years are more likely to support redistribution. In contrast, those who have experienced upward mobility are less likely to support it. Along the same line, Wu and Chou (2017) found that in Hong Kong, people who foresee themselves as more economically vulnerable and identify as being from lower social classes tend to support more government assistance to reduce income inequality. Finally, considering the social values and ideology embraced, Roex *et al.* (2018) and Garcia-Sanchez *et al.* (2019) argued that beliefs in meritocracy, i.e., that individuals' efforts lead to success, might reduce the expectations for income governmental redistribution actions.

Beyond the economic conditions, several studies found a significant and negative impact of each additional year of education in support of equality, indicating that an increase in education years tends to reduce the support for redistribution (Dallinger, 2010; Hjerm & Schnabel, 2012; Roex *et al.*, 2018). Other studies mentioned the role of gender, showing that women tend to favor redistribution more than men (Dallinger, 2010; Hjerm & Schnabel, 2012; Guillaud, 2013; Wulfgramm & Starke, 2016). In a study about the Estonian society, Saar (2008) discussed the role of age, showing that older cohorts in the country tend to be more critical concerning income inequality, with the most important mediator of this effect being justice beliefs (i.e., the perception of existential justice, egalitarian principles, government intervention, capitalist principles, and fair pay ratio). Using data from the European Social Survey, Hjerm and Schnabel (2012) also showed a positive relationship between age and acceptance of taxation and redistribution.

Inequality Perceptions

Perception can be understood as a type of cognition referring to an individual's comprehension of an issue (Aalberg, 2003). In theory, how people perceive the world should be similar to reality. However, studies have identified that there is not always a direct link between changes in real inequality and change in individuals' perceptions of it. For instance, in a study using data from the International Social Survey Program, Osberg and Smeeding (2006) find that subjective estimations of inequality in pay deviate considerably from actual data. When looking at differences between real values and people's estimates, the authors find that actual pay gaps are much larger than what individuals believe.

When looking at the literature on the topic, we can observe that its determinants at the individual level are overall similar to those related to inequality preferences. As Marandola and Xu (2021) indicate, studies examining inequality show a high correlation between perceptions and individuals' observable characteristics, such as their personal income, wealth, education level, and perceived social status. For instance, Poppitz (2018) analyses data from 18 European countries to investigate the determinants of inequality perceptions measured through subjective social status. Their results show that perceived social status is correlated with higher values of income, wealth, years of education, occupation prestige, and parents' social status. In a study using data from the International Social Survey Program conducted by Bavetta *et al.* (2017), the authors find that older respondents and those who consider themselves left in politics tend to report more inequality, while those with middle or high incomes, with a middle or top-class social position, and strong religiosity report low levels of perceived inequality.

The studies mentioned above support the idea that, similar to inequality preferences, inequality perceptions are not only determined by objective and subjective economic factors but also by other individual characteristics, such as social capital, values, and sociodemographic characteristics. In our study, we take a step further and analyze a relationship not yet explored by the literature: the role going abroad has in influencing people's attitudes towards inequality, focusing on a sample of Brazilian students.

Based on the previous evidence about the importance of going abroad in affecting people's personalities, in which mobile students are considered more proficient, approachable, open, agreeable, and less neurotic individuals (Clarke III *et al.*, 2009; Zimmermann & Neyer, 2013; European Union, 2016), we investigate if participating in an exchange program affects students' preferences and perceptions about inequality in their country.

3. DATA AND METHODOLOGY

3.1. DATA: EMPIRICAL SETTING AND DATA SOURCES

We use data from 1,527 (former) students from the University of Campinas (UNICAMP), Brazil, who entered the university between 2010 and 2018. The university was chosen given its tradition of internationalization and the high number of students who go abroad. Since its establishment in the 1960s, internationalization has been part of the university's institutional strategies (Granja & Carneiro, 2020). For instance, between 2010 and 2017, UNICAMP signed more than 500 agreements with foreign institutions involving more than 60 countries (Granja, 2018). UNICAMP was also one of the top ten sending institutions of the Brazilian Science without Borders program, an initiative sponsored by the federal government between 2011 and 2015, which provided more than 90 thousand international mobility grants (Brasil, 2016).

UNICAMP also provides a very well-suited case study given the possible generalization of the research results to the broader Brazilian context. Despite the heterogeneity of higher education institutions in Brazil, UNICAMP is part of an ‘elite’ group of large research-intensive public universities in the country (Schwartzman *et al.*, 2021), which offer the most study opportunities abroad. For example, out of the top ten sending institutions for the Science without Borders program, nine were in the same category as UNICAMP (Brasil, 2016). Thus, considering the involvement of UNICAMP in student mobility programs, we trust that its students can represent Brazilian exchange students and be replicable to other similar institutions in Brazil.

We use two data sources for this study. First, students’ demographic and socioeconomic data at the moment of entering the university and academic information were shared by the university’s Academic Board and International Office after we received the approval of the Brazilian Research Ethics Committee.[3] The remaining data were collected through an online survey administered in May 2021. Using Qualtrics, an invitation was sent to all students who entered university between 2010 to 2020 and had a valid e-mail address.

A total of 18,408 invites were sent, from which we received 2,947 replies (16% response rate).[4] Of those, 2,280 students shared sufficient information. Among those students, 44.6% participated in a student mobility program (treated group), most of them (804 students) during or after university. Among the remaining 55% of students who did not experience mobility (non-treated), more than one-third (473 students) had no intention of applying for an exchange program at any point in their student life. The remaining students applied for a mobility program in the past (327 students), plan to apply in the future (380 students), or both (83 students).

Of the total students sharing sufficient information, we selected the students for our analysis based on two criteria: mobile students who traveled only during or after university and non-mobiles who either applied for exchange programs in the past or showed interest in

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[3] Protocol 25285919.6.0000.8142.

[4] Even though we received almost 3 thousand responses to our online survey, we are aware that a response rate of 16% may impose an issue for the generalization of our results. Thus, in the Appendix A we test the sampling bias, by comparing the exchange students answering the survey to the overall population of exchange student at UNICAMP. The result from our test shows that both samples are very similar in most of their characteristics, having similar academic performance, skin color/race, parents’ education, type of high school, and previous internal mobility experience. Our sample had, however, more females and slightly more students that entered university when they were older. There were also some differences between both groups in their course area, with our sample having more students from Biology and Health Sciences and Humanities.

applying for one in the future (or both). The choice for selecting those students is explained in detail in the Methodology section. We also restricted the analysis to the region of common support, as explained when we discuss the Propensity Score Matching methodology. After applying our inclusion criteria and the selected methodology, our final sample of students narrowed down to 1,527, of which 776 are in the treated and 751 are in the control group.

Table 1 reports the summary statistics of all students in the final sample. We can observe that the sample of students has an average standardized grade in the admission exam of 0.153[5] and entered university at 20 years old on average. Fifteen percent of the students are black/brown/indigenous, 51% are females, 64% with parents that had access to tertiary education, 22% come from public schools (i.e., less prestigious educational institutions in the county), and 15% experienced mobility within the country before entering university. In addition, 51% of the students attended courses in the fields of exact (i.e., hard sciences), technological, and earth sciences, 26% in humanities, 17% in biology and health, and 6% in arts. Most of the students in the sample entered university between 2010 and 2012, and most concluded their courses between 2016 and 2018.

[5] The average standardized grade in the admission exam is calculated using the following formula: (G – A) / SD, where G is the grade of the student (which ranges between 0 and 1000); A is the average grade of the student's cohort (i.e., those entering university in the same year and course); and SD is the standard deviation of the cohort. This standardization strategy is widely used by UNICAMP in recruitment processes (for exchange scholarships, for instance), since it allows for comparison of students from different years and courses.

Table 1 – Summary statistics (final sample)

Variable	Obs.	Mean	Std. dev.	Min.	Max.
Academic ability (grade admission exam, standardized by year and course)	1527	.153	1.063	-2.5	4.651
Race/Skin color (if black, brown or indigenous)	1527	.153	.36	0	1
Gender (if female)	1527	.513	.5	0	1
Age when entering university	1527	19.749	2.62	17	42
Education of the parents (if one or more parents had access to tertiary education)	1527	.64	.48	0	1
Type of high school (if studied only in non-technical public schools)	1527	.216	.412	0	1
Previous internal mobility experience (if completed high school outside the state where UNICAMP is located)	1527	.151	.358	0	1
Course area					
Arts	1527	.058	.234	0	1
Biological Sciences and Health Sciences	1527	.174	.379	0	1
Exact, Technological and Earth Sciences	1527	.509	.5	0	1
Humanities	1527	.259	.438	0	1
Year of admission to university					
2010	1527	.152	.359	0	1
2011	1527	.164	.371	0	1
2012	1527	.152	.359	0	1
2013	1527	.126	.332	0	1
2014	1527	.117	.322	0	1
2015	1527	.116	.32	0	1
2016	1527	.107	.309	0	1
2017	1527	.054	.225	0	1
2018	1527	.012	.111	0	1
Year when leaving university					
2010	1527	.001	.036	0	1
2011	1527	.005	.068	0	1
2012	1527	.006	.077	0	1
2013	1527	.031	.175	0	1
2014	1527	.064	.244	0	1
2015	1527	.11	.313	0	1
2016	1527	.138	.345	0	1
2017	1527	.136	.343	0	1
2018	1527	.138	.345	0	1
2019	1527	.116	.32	0	1
2020	1527	.003	.051	0	1
Still enrolled	1527	.253	.435	0	1

Data source: Authors' estimation from administrative and survey data.

3.2. OUTCOME VARIABLES

We investigate attitudes towards inequality by looking at two dimensions of subjective inequality views: preference and perception.

Inequality Preferences

Inspired by Andersen and Yaish (2012) and Osberg and Smeeding (2005), we estimate an individual coefficient to measure preferences for inequality based on the Gini index.[6]

We consider inequality in terms of salary distribution among different occupations. Respondents are asked how much they believe people with different occupations should earn in Brazil (in local currency per month, before taxes). Those opinions of pay are used to calculate a coefficient representing each respondent's acceptable degree of inequality.

In our study, we use opinions on the incomes of five occupations: general practitioner, president of a large national company, store clerk, unskilled factory worker, and governor of a Brazilian state.[7] The list of occupations is inspired by the approach used in the social inequality questionnaire developed by the International Social Survey Program.[8] The formula used to calculate the coefficient for each individual i is the same one used to calculate the Gini index, and it can be written as follows:

$$G_i = \frac{\sum_{j=1}^{n} \sum_{k=1}^{n} |x_j - x_k|}{2n^2 \bar{x}} \tag{1}$$

Where $x_j - x_k$ is the income differences of all pairs of occupations, n is the total number of occupations and $\bar{x}$ corresponds to the mean of the individual's desired income for all occupations. The index ranges from 0 to 1, with lower values corresponding to a preference for less inequality. A value of zero indicates that the respondent aspires to have all the occupations paid the same.

We chose to use the measure based on the Gini coefficient formula to be able to decompose the index and dig into the mechanisms leading to a certain level of inequality preference. However, we are aware that there are different possible measures for inequality preferences, ranging from more direct questions (such as those used in the World Values Survey[9] and the International Social Survey) to behavioral experiments (such as using a list

[6] The Gini coefficient is one of the most common measures used to summarize inequality in terms of a single number, ranging from 0 (perfect equality) to 1 (perfect inequality) (Jenkins & Van Kerm, 2011).

[7] An English version of the survey question used to measure inequality preference and perception is shown in Appendix B.

[8] The International Social Survey Program is a cross-national program conducting annual surveys about social science topics worldwide. The program currently covers 44 countries and it does not include Brazil as a member state.

[9] The World Values Survey is a cross-country study providing a popular dataset with information about attitudes towards inequality worldwide. It is one of the most used data sources for studies on the topic, given its broad geographical scope (Jaime-Castillo *et al.*, 2016).

experiment to measure sensitive topics).[10] Given the lack of consensus on what is the best way to measure inequality preferences, we test the sensitivity of our results to alternative definitions of inequality preference measures that we extracted from our survey. Appendices C to E report the construction of the alternative measures. Appendix F reports the sensitivity analyses showing that our main conclusions are not sensitive to changes in the individual's inequality preference measure used.

Inequality Perceptions

To measure an individual's perception of inequality, we replicate the strategy detailed above but with a slight variation of the question asked to respondents based on the work done by Andersen and Yaish (2012) and Osberg and Smeeding (2005). In this case, respondents are asked how much they believe people earn in Brazil (instead of how much they should earn). The coefficient calculated represents each respondent's perceived current degree of inequality.

Figure 1 shows the distribution of the preferred and perceived inequality index for mobile and non-mobile students. As we can observe, on average, both mobile and non-mobile students perceive inequality to be higher than they would prefer. Differences between mobile and non-mobile are very small, with mobiles having very similar preferred inequality when compared to non-mobiles while having slightly smaller averages for the perceived inequality coefficient.

[10] More information about (double-) list experiments can be found in Glynn (2013), Lépine *et al.* (2020), Blair and Imai (2012) and Droitcour *et al.* (1991).

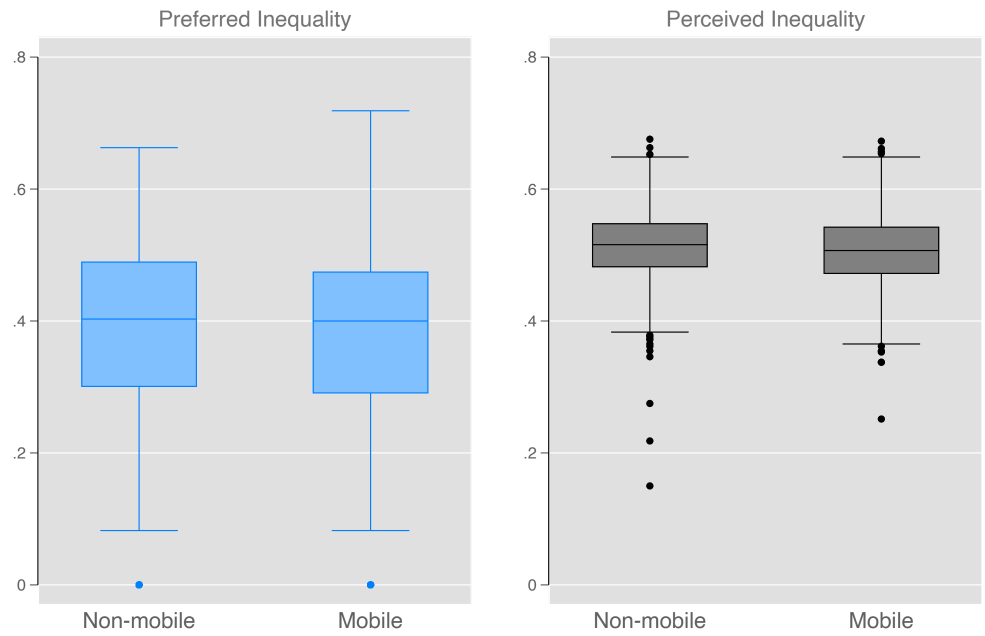

Figure 1 – Preference and perception of inequality by treatment status
Data source: Authors' estimation from administrative and survey data.
Note. Coefficients can take values between 0 (perfect equality) and 1 (perfect inequality). Bars: interquartile range, line: median, dots: outside values. Preference and perception are measured after treatment participation.

Figure 2 shows the disaggregation of the preferred and perceived inequality indexes to the different components, i.e., the salary (preferred and perceived) by occupation. On average, we can observe that both mobile and non-mobile students believe that occupations such as store clerk and unskilled factory worker should earn more than they currently do while acknowledging that the remaining careers should earn less. Differences between mobile and non-mobiles are less visible for occupations requiring lower skills (i.e., store clerk and unskilled factory worker).

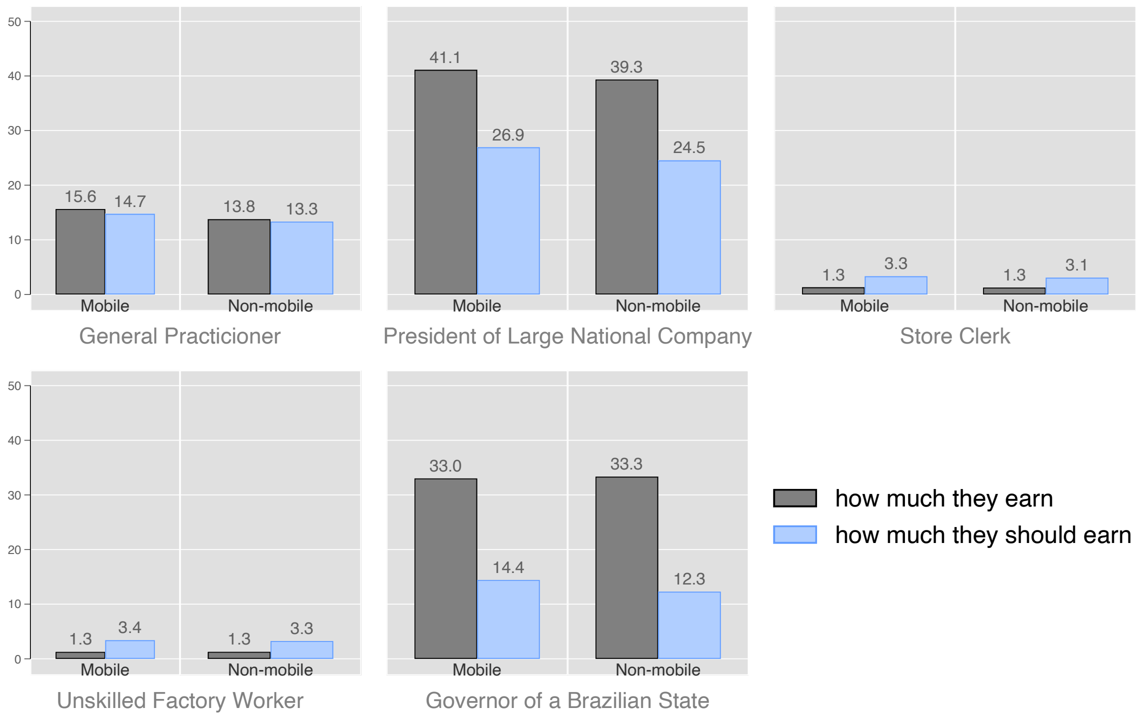

Figure 2 – Disaggregation of preference and perception of inequality by treatment status
Data source: Authors' estimation from administrative and survey data.
Note. Figures represent values in terms of minimum wage.

Interestingly, when comparing the values reported in our sample with the real values earned by those professions in Brazil,[11] we observe that although both groups can estimate properly the values earned by occupations that require less training (such as a store clerk and an unskilled factory worker – that earns approximately 1.4 times the Brazilian minimum wage), they largely underestimate the amount made by a large company president (which is more than 800 times the minimum wage in Brazil). In addition, both groups overestimate the salary of a general practitioner (8.2 times the minimum wage) and a State Governor (21 times).

3.3. METHODOLOGY

It is expected that mobile students have different characteristics than non-mobile students due to selection effects. Minimizing selection effects is one of the biggest challenges in impact evaluation and is already acknowledged in empirical studies assessing the impact of mobility programs (Meya & Suntheim, 2014). To reduce the possible bias due to self-selection and

[11] Real salaries are calculated considering the minimum wage in 2021 of 1100 Brazilian Reais (R$). Salary of a general practitioner, store clerk, and unskilled factory worker retrieved from the portal Salario.com.br (Salário, 2022), which aggregates salary data from official Brazilian sources between August 2021 and July 2022. Salary for State Governor retrieved from the Department of Budget and Management of the Central Unit for Human Resources of the State of São Paulo (UCRH, 2022). Information about the salary of a president of a large national company is estimated using Alvarenga (2020). All salaries (except for the president of a large national company) refer to the average value in the Brazilian State of São Paulo (where UNICAMP is located).

account for the fact that those programs are targeted to a population of students with certain characteristics (e.g., those with better academic performance), we create a control group using Propensity Score Matching (PSM).

PSM is a very flexible statistical impact evaluation technique that can be applied in almost any program, as long as there is a group of nontreated units (Gertler *et al.*, 2016). It works by estimating a probability (propensity score) that each treated unit has of receiving the treatment and using this probability to find one or more similar matches within a control group of nontreated units (Caliendo & Kopeinig, 2008; Gertler *et al.*, 2016). We predict the propensity score through the following equation:

$$E(treatment|X) = P(treatment = 1|X) \tag{2}$$

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 covariates, and E() denotes the mathematical expectation operator.

To identify potential mobile students, we consider as relevant matching characteristics the following: grades on the university admission exam, color/race, gender, age when entering university, parent's education, type of secondary school (public vs. private), previous internal mobility experience, and course area.

We consider color/race, gender, and age as students' demographic characteristics. Those characteristics are added to account for any possible systematic differences between students with different demographic profiles in their choice of going abroad.

Parent's education and type of secondary school (public vs. non-public) are added to account for students' socioeconomic background since students from higher-income families may be more likely to pursue part of their studies abroad (Junor & Usher, 2008; Meya & Suntheim, 2014; European Union, 2016). Studies also show that first-generation college students may have many responsibilities, such as working full-time or being married, that can compete with the time devoted to study (Warburton, Bugarin & Nuñez, 2001; Eveland, 2020) and affect participation in mobility programs. In addition, highly educated parents might indirectly influence their children to go abroad by highlighting the benefits of international mobility to them (Meya & Suntheim, 2014; Di Pietro, 2019). Socioeconomic characteristics are also added because they may correlate to people's opinions on reducing inequality, as the literature discussed previously shows.

Previous internal mobility experience is added because this kind of experience might affect students' participation in mobility programs. For example, students who have already left their social environment once may be more likely to move to another country and invest a great number of resources in finding the perfect match regarding university and field of study (Meya & Suntheim, 2014).

Grades on the admission exam are added to account for students' academic ability, as those who apply for an exchange may be academically more able and motivated than others (Meya & Suntheim, 2014), having higher chances of being awarded a grant to go abroad.

Finally, we account for the course area. During 2011 and 2015, 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 Biological Sciences, Health, Exact, Technological, and Earth Sciences, a dummy variable is added to account for those subject areas.

Table 2 shows that mobile and non-mobile students of the full list of respondents differ significantly in their baseline characteristics. For example, mobile students have higher pre-university grades, are younger when entering university, have better economic conditions (i.e., more educated parents and study more in private schools), and experience more mobility before entering university than non-mobile students. There are also differences in the distribution of the areas of their studies. For instance, Exact, Technological, and Earth Sciences students tend to be more mobile. Male students and black/brown/indigenous students tend to move less.

Table 2 – Comparison between mobile and non-mobile students (baseline variables)

	(1) Mobile students	(2) Non-mobile students	t-value (1) vs. (2)
Grade admission exam (standardized)	0.325	0.008	6.700***
Black, brown, or indigenous	0.117	0.179	-3.730***
Female	0.524	0.458	2.930***
Age when entering university	19.662	20.263	-3.950***
One or more parents had access to higher education	0.707	0.576	5.980***
Public high school	0.170	0.263	-4.920***
Previous internal mobility experience	0.175	0.127	3.010***
Course area			
Arts	0.056	0.058	-0.170
Biological Sciences and Health Sciences	0.129	0.201	-4.220***
Exact, Technological and Earth Sciences	0.570	0.481	3.930***
Humanities	0.245	0.260	-0.750

Data source: Authors' estimation from administrative and survey data.
Note. Figures calculated using the full sample of the survey respondents (n = 2,280). *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

To ensure that none of the matching variables could be affected by having participated in mobility programs, which could bias our results (Gertler *et al.*, 2016), we restrict the sample of mobility students to those who traveled only after entering university. By focusing on those students, we guarantee that treatment participation does not affect the variables included in the propensity score calculation (that are measured when students enter university). In addition, to reduce the bias due to potential self-selection into mobility programs caused by unobserved or omitted factors, the control group only contains non-mobile students who either applied for mobility programs in the past or show interest in applying for one in the future.[12] By doing that, we control for the fact that students interested in mobility may be more motivated than those not interested in going abroad.

We explore the impact of student mobility programs on our outcomes of interest 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 variables (Y) can be formally specified as follows:

[12] To capture that, we included a question in the survey asking whether the person has applied for mobility in the past or plan to apply in the future.

$$ATT = E(Y^T|D = 1) - E(Y^C|D = 0) \quad (3)$$

Where Y^T denotes the potential outcomes for the treated individuals; Y^C denotes the potential outcomes for the nontreated individuals; D is a dummy for student mobility status; $E()$ indicates the mathematical expectation operator.

Our model is given by:

$$Y_i = \beta_1 + \beta_2 treatment_i + X_i + \varepsilon_i \quad (4)$$

Where Y_i stands for the outcome variable of student i ; *treatment* is a dummy variable that takes the value of 1 if student i participated in a student mobility program; X_i is a set of individual covariates of student *i*; and ε_i is the error term. β_2 represents the average treatment effect. To apply PSM, the regression uses weights based on the propensity score (*p*), which is 1/*p* for a treated participant and 1/(1-*p*) for a control participant. Propensity score weighting is equivalent to a weighted analysis treating propensity score weights as sampling weights (Guo & Fraser, 2015).[13]

The rationale for using PSM to create an artificial control group instead of doing a pure experiment is mainly that doing an experimental framework (such as a Randomized Control Trial), where students are randomly assigned to study abroad, is 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. UNICAMP has several mobility programs, and students are not limited to only applying to one. Using Difference-in-Differences is also not possible in this case since there is no baseline information on our outcomes of interest, and it was not feasible to collect data prior to mobility, given that this research was conducted during the COVID-19 pandemic when most mobility programs were suspended or postponed.

Nevertheless, we are aware that using PSM leads to unbiased and robust results only if two assumptions hold: conditional independence (also called unconfoundedness or selection

[13] We are aware that there are several other possible matching techniques that can be used when doing matching, that may differ in the way the neighborhood for each treated unit is defined, and the common support is handled, and regarding the weights that are assigned to these neighbors (Caliendo & Kopeinig, 2008). With that in mind, in Appendix G, we test the robustness of our main results regarding the choice of different matching methods. We compare results from the original linear model calculated using sample weights based on the propensity score with other matching techniques such as Kernel, 5-Nearest Neighbors, and Coarsened Exact Matching. Our results show that our main conclusions remain the same regardless of the choice of algorithm/technique to perform the matching.

on observables) and common support (also called overlap). We discuss those two assumptions below.

Conditional independence

The first assumption 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 & Kopeinig, 2008). It can be written as follows:

$$(Y_T, Y_C) \perp\!\!\!\perp \mathrm{D} \mid \mathrm{X} \tag{5}$$

Where ⫫ denotes independence.

The conditional independence assumption cannot be directly tested. However, extensive information on treatment selection helps define a set of covariates, which makes the assumption more probable, with the model including variables that determine the probability of going abroad (Rosenbaum & Rubin, 1983; González & Pazó, 2008; Gertler *et al.*, 2016).

Even without the possibility of testing this assumption empirically, we are confident that, in our case, the most important pre-treatment characteristics to determine participation in mobility programs are considered. For instance, by including the grades in the admission exam, we are accounting for students' academic performance, one of the most important criteria used by higher education institutions to select their exchange students. When adding socioeconomic variables, we account for one of the main challenges preventing students from going abroad: the lack of financial resources (Junor & Usher, 2008). By adding demographic characteristics, we account for possible 'hidden' criteria affecting less privileged students' motivation and access to study-abroad opportunities. Finally, when adding a variable to account for the course area, we capture the differences in the number of scholarships available for each field of study.

By adding all those variables, we believe that the relevant factors that might impact treatment assignment are observed. In addition, by limiting the control group only to students interested in going abroad (i.e., those who applied for a program in the past or plan in the future), we control for potential self-selection to mobility caused by factors not observed in this study.

Common support

The common support assumption states that units with a given set of 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:

$$0 < P(D = 1|X) < 1 \tag{6}$$

We test this assumption by visualizing the density distribution of the propensity score in both the treatment and control groups, as discussed by Caliendo and Kopeinig (2008). Figure 3 shows the distribution of the propensity scores for both groups. As expected, the treated group has their distribution of propensity scores more skewed to the left, while the controls are more skewed to the right. Overall, the common support assumption is fulfilled, with 96.5% (776 out of 804) treated observations within the common support area.

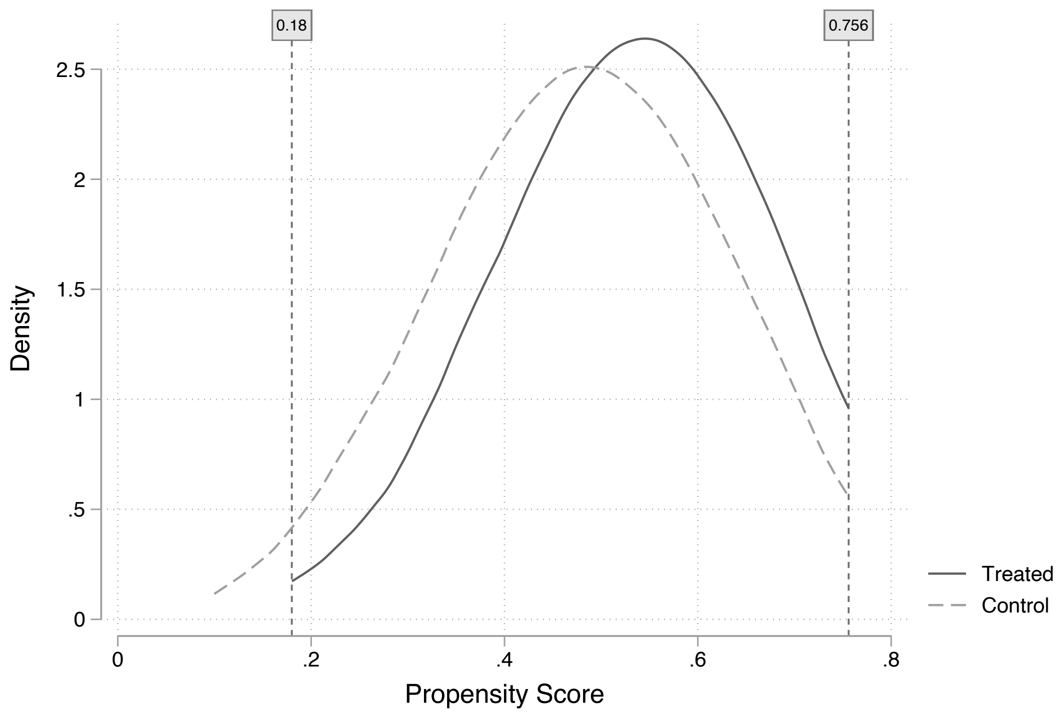

Figure 3 - Distribution of the propensity scores for treatment and control groups (Common Support Assumption)
Data source: Authors' estimation from administrative and survey data.

4. RESULTS

4.1. PROPENSITY SCORE ESTIMATION

Table 3 displays the model's results used to predict the propensity score (through Equation 2). The dependent variable is a binary variable taking the value 1 if the student participated in a mobility program and 0 otherwise. The set of independent variables used are those discussed in the Methodology section.

Table 3 – Participation in student mobility programs (probit model)

Dependent variable: Pr(Student Mobility = 1)	Coefficients		Marginal Effects		Sig.
	coef.	std. err.	dy/dx	std. err.	
Academic ability (if the grade in the admission exam is higher than the average of the same year and course)	0.288	0.066	0.115	0.026	***
Race/Skin color (if black, brown or indigenous)	-0.302	0.093	-0.121	0.037	***
Gender (if female)	0.131	0.067	0.052	0.027	*
Age when entering university	0.021	0.082	0.008	0.033	
Age when entering university (squared)	-0.001	0.002	-0.000	0.001	
Education of the parents (if one or more parents had access to tertiary education)	0.309	0.07	0.123	0.028	***
Type of high school (if studied only in non-technical public schools)	-0.207	0.083	-0.082	0.033	**
Previous internal mobility experience (if completed high school outside the state where UNICAMP is located)	0.252	0.094	0.101	0.037	***
Course area (if eligible for the SwB program, i.e., enrolled in Biological Sciences, Health, Exact, Technological or Earth Sciences)	0.084	0.074	0.034	0.029	
Constant	-0.473	0.989			
Number of observations	1527				
Pseudo r-squared	0.039				
Chi-square	77.540				
Prob > chi^2	0.000				

Data source: Authors' estimation from administrative and survey data.
Note. Marginal effects are calculated at the means of covariates; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

Results show that all variables, except age and course area, significantly correlate to the probability of participating in a student mobility program. Higher pre-university grades, being female, having more educated parents, and having previous mobility experience 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, those who self-declared as black/brown/indigenous and those who attended only public schools before entering university are negatively associated with the conditional probability of being in the treatment group. Those results are not surprising, given that mobility programs in Brazil tend to benefit students from more privileged backgrounds (Borges, 2015; Gomes, 2020; Lopes, 2020; Feltrin *et al.*, 2021).

4.2. BALANCING TEST FOR PSM ESTIMATIONS

After estimating the propensity scores for each sample unit, we test the balancing property of the observed covariates between the treatment and control groups and the overall balance. The goal is to check if the sampling bias is reduced through matching.

The results presented in Table 4 show a bias reduction after matching. It indicates that the matching sufficiently balances most covariates (except for academic ability and parent's education) and considerably reduces initial differences of both treated and untreated. The table also compares the joint significance of all matching variables of the probit model. The Pseudo R-squared of results after matching is lower for the matched sample than for the unmatched one. The mean and the median of the absolute standardized bias are reduced.

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) fall within the bounds suggested by Rubin (2001). Results indicate that the samples became sufficiently balanced after matching. Nevertheless, to account for any remaining imbalance (especially caused by the academic ability and parent's education variables), all variables used to estimate the propensity score will be added to one of the specifications of the outcome regression model as a robustness check.

Table 4 – Balancing results before and after matching

Variable	Sample	Mean Treated	Mean Control	Bias (%)	↓ Bias (%)	p>t
Academic ability (if the grade in the admission exam is higher than the average of the same year and course)	Unmatched	.56095	.45316	21.7		0.000
	Matched	.55541	.50163	10.8	50.1	0.090
Race/Skin color (if black, brown or indigenous)	Unmatched	.11705	.19346	-21.2		0.000
	Matched	.11727	.14754	-8.4	60.4	0.153
Gender (if female)	Unmatched	.52363	.48987	6.8		0.178
	Matched	.53093	.51331	3.5	47.8	0.580
Age when entering university	Unmatched	19.662	19.956	-10.7		0.032
	Matched	19.585	19.723	-5.0	53.2	0.366
Age when entering university (squared)	Unmatched	393.05	406.78	-10.0		0.047
	Matched	389.02	395.29	-4.5	54.3	0.394
Education of the parents (if one or more parents had access to tertiary education)	Unmatched	.70738	.57106	28.7		0.000
	Matched	.70747	.64495	13.1	54.1	0.034
Type of high school (if studied only in non-technical public schools)	Unmatched	.1704	.26456	-23.0		0.000
	Matched	.17397	.21237	-9.4	59.2	0.122
Previous internal mobility experience (if completed high school outside the state where UNICAMP is located)	Unmatched	.17537	.13165	12.1		0.015
	Matched	.17526	.14553	8.3	32.0	0.210
Course area (if eligible for the SwB program, i.e., enrolled in Biological Sciences, Health, Exact, Technological or Earth Sciences)	Unmatched	.699	.66456	7.4		0.140
	Matched	.69845	.67919	4.1	44.1	0.513

Sample	Pseudo R^2	LR chi^2	p>chi^2	Mean Bias	Median Bias	B	R
Unmatched	0.039	82.30	0.000	15.7	12.1	47.1*	0.88
Matched	0.009	13.28	0.150	7.5	8.3	23.3	1.01

Data source: Authors' estimation from administrative and survey data.
Note. * if B>25% or R outside [0,5; 2].

4.3. AVERAGE TREATMENT EFFECTS ON THE TREATED

In our analysis, we consider the impact of students' mobility on preferred and perceived inequality, respectively.

The impact of students' mobility on preferred inequality

Table 5 shows the propensity score weighted linear regression results for the variable measuring preferred inequality. It indicates that, on average, mobility has no significant effect on preferred inequality at any acceptable significance level.

Table 5 – Average treatment effect on the treated, preferred inequality

	(I)	(II)
Preferred inequality	-.0037983	-.0038001
	(.0074413)	(.007199)
Untreated	751	751
Treated	776	776
PSM covariates	No	Yes

Data source: Authors' estimation from administrative and survey data.
Note. Average treatment effect calculated through a linear model using weights based on the propensity score; standard errors in parentheses; only observations on common support are used; (I) corresponds to the model with no covariates and (II) corresponds to the regression including all matching covariates; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

Despite the insignificant overall results, we can observe some interesting trends when investigating the impact of international mobility on the five components used to calculate the preferred inequality coefficient (Table 6). Results show that although mobility does not affect preference to reduce inequality, it affects the preferences on the incomes of several occupations. In general, mobile students prefer higher salaries than non-mobile, with those who go abroad preferring to see higher salaries for higher-skilled jobs, such as general practitioners, company presidents, and politicians.

Table 6 – Average treatment effect on the treated, preferred income disaggregation

Preferred income	General practitioner		President large nat. company		Store clerk		Unskilled factory worker		Brazilian state governor	
	(I)	(II)	(I)	(II)	(I)	(II)	(I)	(II)	(I)	(II)
	1.446 ***	1.446 ***	2.433 ***	2.428 ***	.231 **	.230 **	.164	.161	1.946 ***	1.953 ***
	(.476)	(.474)	(.786)	(.759)	(.113)	(.112)	(.122)	(.121)	(.554)	(.548)
Untreated	751	751	751	751	751	751	751	751	751	751
Treated	776	776	776	776	776	776	776	776	776	776
PSM covariates	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Data source: Authors' estimation from administrative and survey data.
Note. Average treatment effect calculated through a linear model using weights based on the propensity score; standard errors in parentheses; only observations on common support are used; (I) corresponds to the model with no covariates and (II) corresponds to the regression including all matching covariates; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

The impact of students' mobility on perceived inequality

In Table 7, we show the results for the average treatment effects of international mobility on perceived inequality. Contrary to the preferred inequality variable, in this case going abroad significantly impacted people's view on perceived inequality, with the treatment group believing that current inequality in the country is slightly smaller than non-mobile students with similar pre-treatment characteristics.

Table 7 – Average treatment effect on the treated, perceived inequality

Perceived inequality	(I)	(II)
	-.0089182***	-.0089028***
	(.0029684)	(.0029578)
Untreated	751	751
Treated	776	776
PSM covariates	No	Yes

Data source: Authors' estimation from administrative and survey data.
Note. Average treatment effect calculated through a linear model using weights based on the propensity score; standard errors in parentheses; only observations on common support are used; (I) corresponds to the model with no covariates and (II) corresponds to the regression including all matching covariates; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

When investigating the results further (Table 8), we can observe some differences in income perceptions, with mobile students believing, on average, that the current income of some occupations (such as a general practitioner and a company president) is higher than what their matched counterparts observe.

Table 8 – Average treatment effect on the treated, perceived income disaggregation

Perceived income	General practitioner		President large nat. company		Store clerk		Unskilled factory worker		Brazilian state governor	
	(I)	(II)	(I)	(II)	(I)	(II)	(I)	(II)	(I)	(II)
	1.780 ***	1.774 ***	1.459 **	1.448 **	.021	.021	.012	.012	-.415	-.413
	(.510)	(.508)	(.613)	(.602)	(.076)	(.076)	(.043)	(.042)	(.618)	(.611)
Untreated	751	751	751	751	751	751	751	751	751	751
Treated	776	776	776	776	776	776	776	776	776	776
PSM covariates	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Data source: Authors' estimation from administrative and survey data.
Note. Average treatment effect calculated through a linear model using weights based on the propensity score; standard errors in parentheses; only observations on common support are used; (I) corresponds to the model with no covariates and (II) corresponds to the regression including all matching covariates; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

4.4. DIGGING INTO GROUP HETEROGENEITY

To capture potential heterogeneity among different groups of students, in this section, we disaggregate the results by the characteristics of the mobility experienced and students' characteristics.

4.4.1. CHARACTERISTICS OF THE MOBILITY EXPERIENCED

When disaggregating the treatment effects by the characteristics of the mobility experienced (i.e., factors that policymakers can adjust when designing their programs) such as destination region, date of the exchange, and course area, we observe that results for the preferred inequality variable remain insignificant for most student subgroups (Table 9). The only exception happens in the case of students traveling to North America, who show higher acceptance of inequality.

Results for the perceived inequality variable, however, show some subgroup variations. Students traveling to North America and Europe, those who returned from the exchange less than five years ago (or who are still abroad), and those not enrolled in arts and humanities all observe less inequality compared to the remaining subgroups. Coefficients, however, are small.

Table 9 - Average treatment effect on the treated by characteristics of the mobility experienced

	Region of destination			End of last exchange		Course area	
	North America	Europe	Others	More than 5 years	Last 5 years	Biology, Health, Exact, Technology and Earth	Arts and Humanities
Preferred inequality	.024** (.012)	-.012 (.008)	-.006 (.015)	.003 (.009)	-.011 (.009)	-.010 (.008)	.009 (.014)
Perceived inequality	-.015*** (.005)	-.011*** (.003)	.007 (.005)	-.006* (.004)	-.012*** (.004)	-.011*** (.004)	-.005 (.005)

Data source: Authors' estimation from administrative and survey data.
Note. Average treatment effect calculated through a linear model using weights based on the propensity score; standard errors in parentheses; only observations on common support are used; estimations based on the model with no covariates; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level; course area aggregated based on eligibility to the Science without Borders program.

4.4.2. PRE-TREATMENT VARIABLES

Table 10 shows the results of the disaggregation based on pre-treatment socioeconomic characteristics. Almost all subgroups show insignificant effects of going abroad on the preferred inequality variable. The only exception happens in the case of the respondent's age, with older mobile students preferring slightly less inequality.

In the case of the perceived inequality variable, we observe that students coming from more disadvantaged economic backgrounds (i.e., with less educated parents and coming from public schools), as well as females, non-black/brown/indigenous, and those that are less than

30 years old respond differently from going abroad when compared to the remaining subgroups. Students with those characteristics, when going abroad, present slightly smaller coefficients for the perceived inequality variable when compared with non-mobiles with similar characteristics.

Table 10 – Average treatment effect on the treated by socioeconomic characteristics

	Parents education		Secondary school type		Gender		Skin color/race		Current age	
	More educ.	Less educ.	Public	Non-public	Fem.	Male	Black, brown or ind.	Others	< 30	≥ 30
Preferred inequality	-.002 (.010)	-.007 (.012)	-.005 (.016)	-.003 (.008)	-.010 (.010)	.003 (.010)	-.008 (.019)	-.003 (.008)	.005 (.008)	-.045** (.019)
Perceived inequality	-.006 (.004)	-.014*** (.005)	-.012* (.006)	-.008** (.003)	-.013*** (.004)	-.005 (.004)	.002 (.008)	-.011*** (.003)	-.011*** (.003)	-.000 (.007)

Data source: Authors' estimation from administrative and survey data.
Note. Average treatment effect calculated through a linear model using weights based on the propensity score; standard errors in parentheses; only observations on common support are used; estimations based on the model with no covariates; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

4.4.3. POST-TREATMENT VARIABLES

In this section, we investigate possible heterogeneous effects of treatment participation on subgroups with different post-treatment economic statuses (Table 11) and distinct perceptions of their well-being (Table 12).

Results show that the effect of going abroad is overall insignificant for most subgroups. However, it varies depending on the individual current income and occupation. Mobility is associated with preferences to reduce inequality only in groups reporting lower current incomes and working outside the private sector.

In the case of the variable measuring perceptions, we observe negative and significant coefficients in students in the middle of the income distribution and those working outside the private sector. Along the same line, when classifying the students into different groups according to their self-reported current well-being, treated respondents who regarded themselves as having higher well-being believe that inequality is smaller in Brazil compared to the control group. In contrast, no difference is found for those who rate themselves as having lower or medium well-being. A similar trend happens for those who believe they experienced upward social mobility in the past five years and those who expect upward social mobility in the near future. Both mobility groups perceive inequality to be lower, whereas there are no significant effects of mobility on those that experienced or expected downward or no change in their social mobility.

Table 11 – Average treatment effect on the treated by economic status

	Current per capita income+			Occupation	
	< 5 min. wage	5-10 min. wage	> 10 min. wage	Private sector	Others
Preferred inequality	-.026*** (.010)	.009 (.014)	-.017 (.023)	-.001 (.009)	-.022* (.013)
Perceived inequality	-.006 (.004)	-.010* (.006)	-.005 (.010)	-.005 (.004)	-.013** (.005)

Data source: Authors' estimation from administrative and survey data.
Note. Average treatment effect calculated through a linear model using weights based on the propensity score; standard errors in parentheses; only observations on common support are used; estimations based on the model with no covariates; + current per capita income calculated dividing the monthly household income (in minimum wages at the date of the survey) by the number of people in the household; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

Table 12 – Average treatment effect on the treated by well-being perception[14]

	Experienced social class change (past 5 years)			Expected social class change (future 5 years)			Current well-being		
	Down	None	Up	Down	None	Up	Low	Middle	High
Preferred inequality	.009 (.020)	-.013 (.017)	-.008 (.009)	-.008 (.042)	.005 (.020)	-.008 (.008)	-.003 (.021)	-.015 (.019)	-.010 (.009)
Perceived inequality	-.007 (.007)	-.002 (.007)	-.011 *** (.004)	-.013 (.012)	-.003 (.008)	-.009 *** (-.009)	-.000 (.007)	-.006 (.007)	-.009 *** (.004)

Data source: Authors' estimation from administrative and survey data.
Note. Average treatment effect calculated through a linear model using weights based on the propensity score; standard errors in parentheses; only observations on common support are used; estimations based on the model with no covariates; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

While results from the heterogeneity analysis on post-treatment variables seem interesting, we emphasize that they should be interpreted exclusively as correlation and not as causal as those variables were measured after students went abroad, being potential outcome variables per se. Given that they could have been affected by treatment participation (but not

[14] The three groups are defined based on the answers to the question: "On a scale of 0 to 10, in which 0 are the people with the lowest income and quality of life, and in 10 are the people with the highest income and quality of life, in what position would you put yourself following moments of your life?". Respondents have to select a number from 0 to 10 for their position in the 'current moment', '5 years ago' and '5 years from now'. By comparing those values, we know if respondents experienced/expect an improvement or not in their social class.

affect treatment status), they were not considered in our main propensity score matching estimation, only being added to investigate potential heterogeneous effects.

5. DISCUSSION

Inequality Preferences

The literature on student mobility claims that going abroad can improve people's personalities and cross-cultural skills. Mobile students appear more proficient, approachable, open, agreeable, and less neurotic individuals (Clarke III *et al.*, 2009; Zimmermann & Neyer, 2013; European Union, 2016). However, our results point us in a different direction when looking at students' inequality preferences. Against our expectations, our results show that going abroad does not affect students' preference to reduce inequality.

Still, we observe interesting trends when grouping students based on selected pre- and post-treatment characteristics. For instance, when looking at economic characteristics, we observe that mobility affects the inequality preferences of students reporting lower current incomes. For those students, mobility is associated with significant preferences to reduce inequality.

Even though our data does not allow us to determine precisely the causal mechanisms behind this result, economic theory can help us build a possible explanation. The self-interest approach states that even when the current level of inequality is seen as legitimate by individuals, people tend to support a decrease in inequality if they might benefit from it (Meltzer & Richard, 1981; Curtis & Andersen, 2015; Garcia-Sanchez *et al.*, 2019). Inspired by this approach, we argue that self-interest is one possible reason mobility affects the preferences of those students in worse economic conditions more than the preferences of other groups.

When looking at the effect of student mobility on current income and perceived well-being, we observe that, in line with previous studies (Di Pietro, 2013; Engberg *et al.*, 2014), exchange students have higher current incomes and higher self-assessed well-being (Appendix H). Students who fail to meet their financial expectations towards mobility programs might believe that inequality affects them directly, becoming more concerned about inequality than others.

When disaggregating the inequality measures, we observe that mobile students prefer higher salaries for more skilled occupations. This latter result might be explained by the tendency to interpret the fact of being awarded a mobility grant as a proxy for academic excellence (Engberg *et al.*, 2014). Considering the competitive nature of mobility programs, awardees might put themselves in the shoes of the most successful individuals, i.e., those with privileged occupations, and express their preferences for advantaging those occupations believing they would benefit from a rise in those salaries.

Inequality Perceptions

When looking at the impact of going abroad on mobile students' perceived inequality, we find that both mobile and non-mobile students underestimated the real wage inequality in Brazil. However, mobile students believe that the current income disparities in the country are slightly smaller than non-mobile students.

Several scholars tried to explain why people underestimate economic inequality. Those scholars attribute the reason to either ignorance or indifference, suggesting that since an individual's perception of reality is limited to their immediate social and geographic environment, an underestimation of inequality can happen if one's reality has fewer disparities than the national context (Becker, 2021). It might be the case that mobile students, while abroad (or even upon returning), mostly interact with peers with better economic conditions, generating a detachment from their country's reality and leading them to underestimate inequality more than the non-mobiles.

For instance, mobile students believe that the current income of some highly skilled occupations is higher than what their non-mobile matched counterparts observe. It might be that mobile students observe the lifestyles of professionals abroad, where salaries are usually higher than the Brazilian ones, and detach from their national reality.

Interestingly, we also observe that individuals' attitudes affect perceptions toward inequality. In particular, students who are more 'positive' towards their economic status (i.e., those with higher self-assessed well-being and those who either experienced or expected upward social mobility) are the ones for which mobility significantly affected perceived inequality. We may conjecture that more optimistic students are more inclined to 'view the world through a better lens' and are more susceptible to changing their inequality views after experiencing a different reality.

*

The literature on both student mobility and people's attitudes toward inequality is extensive, and the interpretation of the causal mechanisms behind human preferences and perceptions is not straightforward. In this section, we provided some conjectures to explain part of our results. Still, further research is needed to test our theories in a more empirical setting and explain the remaining heterogeneity of its effects.

6. CONCLUSION

This study investigates the role of international mobility on students' attitudes towards inequality, focusing on two dimensions: preference and perception of inequality. We complement secondary data with data collected by interviewing more than a thousand former students from a Brazilian university. To assess the causal impact of mobility, we implement Propensity Score Matching and construct an artificial group of non-mobile students to compare with the mobile ones. To the best of our knowledge, this is the first study addressing empirically the impact of going abroad on individuals' views on inequality.

Results show that going abroad does not affect students' preference to reduce within-country inequality. Still, it affects salary preferences, with exchange students expressing their preferences favoring higher salaries for high-skilled jobs. We also found a significant effect of going abroad on individuals' perception of current inequality, with mobile students underestimating inequality more than their non-mobile counterparts.

Mobility programs are understood in the academic literature as a policy instrument that can positively impact students in several aspects, including personal development (Clarke III *et al.*, 2009; Zimmermann & Neyer, 2013; European Union, 2016). Our results present empirical evidence that challenges this idea since mobility does not affect students' preference to reduce inequality. Considering the unequal Brazilian society, our results are worrying, and they invite us to reflect on student mobility programs' role in generating caring future decision-makers.

This study is not exempt from limitations. First, the data collection was performed during the COVID-19 pandemic, a period during which mobility programs were either postponed or canceled. Hence, the PSM technique was the most appropriate methodology for comparing groups of mobile and non-mobile students. Even though PSM is a widely used and flexible statistical impact evaluation technique, we believe future research should validate our results using different (quasi-) experimental designs, such as randomized control trials (if feasible), difference-in-differences, and/or a regression discontinuity design. For that, having information on students' views on inequality before mobility would be desirable to improve the statistical model.

Another limitation is that, even though UNICAMP's exchange students can represent the average mobile student in Brazil (as discussed in the Data and Methodology section), students (mobile or not) at Brazilian 'elite' institutions usually come from more privileged strata of society. At those universities, enrolment is typically associated with students' socioeconomic backgrounds. In our sample, for instance, most students had parents that had access to tertiary education, with the minority being black/brown/indigenous or coming from public schools (i.e., less prestigious institutions and those with more deprived students). Having that in mind, we believe it would be beneficial for policy purposes if future research about the effects of mobility on inequality attitudes focus on more underprivileged students.

To the best of our knowledge, our study is the first to address the impact of mobility on inequality views. Hence, conducting the same study in countries other than Brazil is crucial to understanding the possible (if any) heterogeneity of the impacts on students from different country contexts.

References

Aalberg, T. (2003). Perceived Distributions: The Public Understanding of Reality. In *Achieving Justice: Comparative Public Opinion on Income Distribution* (Chapter 5). Brill.

Alvarenga, D. (2020). *No Brasil, CEO de empresa de capital aberto ganha em média 75 vezes mais que funcionários*. G1. Retrieved September 14, 2022 from https://g1.globo.com/economia/noticia/2020/09/30/no-brasil-ceo-de-empresa-de-capital-aberto-ganha-em-media-75-vezes-mais-que-funcionarios.ghtml

Andersen, R., & Yaish, M. (2012). Public Opinion on Income Inequality in 20 Democracies: The Enduring Impact of Social Class and Economic Inequality. *AIAS, GINI Discussion Paper*, 48.

Andrade, R. O. (2019). Brazil budget cuts threaten 80,000 science scholarships. *Nature*, 572(7771), 575–576.

Bavetta, S., Donni, P. L., & Marino, M. (2017). An empirical analysis of the determinants of perceived inequality. *Review of Income and Wealth*.

Becker, B. (2021). Temporal change in inequality perceptions and effects on political attitudes. *Political Research Exchange*, 3(1), 1860652.

Blackwell, M., Iacus, S., King, G., & Porro, G. (2009). cem: Coarsened exact matching in Stata. *The Stata Journal*, 9(4), 524–546.

Blair, G., & Imai, K. (2012). Statistical analysis of list experiments. *Political Analysis*, 20(1), 47–77.

Borges, R. A. (2015). *A interseccionalidade de gênero, raça e classe no Programa Ciência sem Fronteiras: um estudo sobre estudantes brasileiros com destino aos EUA* [Master's thesis, Universidade de Brasília].

Brasil. (2016). *Science without Borders Control Panel*. Retrieved March 21, 2016, from http://www.cienciasemfronteiras.gov.br/web/csf/painel-de-controle.

Bullock, J. G., Gerber, A. S., Hill, S. J., & Huber, G. (2015). Partisan bias in factual beliefs about politics. *Quarterly Journal of Political Science*, 10(4), 519–578.

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of economic surveys*, 22(1), 31–72.

Cappelen, A. W., Haaland, I. K., & Tungodden, B. (2018). *Beliefs about Behavioral Responses to Taxation*. Mimeo, pp. 1–21.

Casara, B. G. S., Filippi, S., Suitner, C., Dollani, E., & Maass, A. (2022). Tax the élites! The role of economic inequality and conspiracy beliefs on attitudes towards taxes and redistribution intentions. *British Journal of Social Psychology*.

Clarke III, I., Flaherty, T. B., Wright, N. D., & McMillen, R. M. (2009). Student intercultural proficiency from study abroad programs. *Journal of Marketing Education*, 31(2), 173–181.

Contu, G., Frigau, L., Mola, F., Romano, M., & Conversano, C. (2020). University student achievements and international mobility - The case of University of Cagliari. *Electronic Journal of Applied Statistical Analysis*, 13(2), 474–497.

Curtis, J., & Andersen, R. (2015). How Social Class Shapes Attitudes on Economic Inequality: The Competing Forces of Self-Interest and Legitimation. *International Review of Social Research 2015*, 5(1), 4–19.

Dallinger, U. (2010). Public support for redistribution: What explains cross-national differences? *Journal of European Social Policy*, 20(4), 333–349.

De Negri, F. (2021). *Políticas Públicas para Ciência e Tecnologia no Brasil: cenário e evolução recente*. Instituto de Pesquisa Econômica Aplicada (Ipea), Brasilia, Brazil.

Di Pietro, G. (2013). Do Study Abroad Programs Enhance the Employability of Graduates? *IZA (Institute for the Study of Labor) Discussion Papers Series*.

Di Pietro, G. (2019). University study abroad and graduates' employability. *IZA World of Labor 2019*, 109, https://doi.org/10.15185/izawol.109.v2

Droitcour, J., Caspar, R. A., Hubbard, M. L., Parsley, T. L., Visscher, W., & Ezzati, T. M. (1991). The item count technique as a method of indirect questioning: A review of its development and a case study application. In *Measurement errors in surveys*, pp. 185–210.

Engberg, D., Glover, G., Rumbley, L., & Altbach, P. (2014). *The rationale for sponsoring students to undertake international study: an assessment of national student mobility scholarship programmes*. Retrieved August 15, 2022, from http://www.britishcouncil.org/sites/britishcouncil.uk2/files/e002_outward_mobility_study_final_v2_web.pdf

European Union. (2016). *The Erasmus Impact Study: Regional Analysis*. Luxembourg, Publications Office of the European Union.

Eveland, T. J. (2020). Supporting first-generation college students: analysing academic and social support's effects on academic performance. *Journal of Further and Higher Education*, 44(8), 1039–1051.

Feltrin, R. B., Santos, D. F. D., & Velho, L. M. L. S. (2021). O papel do Ciência Sem Fronteiras na inclusão social: análise interseccional do perfil dos beneficiários do programa na Unicamp. *Avaliação: Revista da Avaliação da Educação Superior*, 26, 288–314.

Garcia-Sanchez, E., Obsorne, D., Willis, G. B., & Rodriguez-Bailon, R. (2019). Attitudes towards redistribution and the interplay between perceptions and beliefs about inequality. *British Journal of Social Psychology*, pp. 1–26.

Gertler, P. J., Martinez, S., Premand, P., Rawlings, L. B., & Vermeersch, C. M. J. (2016). *Impact evaluation in practice*. The World Bank, Second edition.

Glynn, A. N. (2013). What can we learn with statistical truth serum? Design and analysis of the list experiment. *Public Opinion Quarterly*, 77, 159–172.

Gomes, C. B. T. (2020). O efeito do capital escolar no acesso ao Programa Ciência sem Fronteiras. *ETD-Educação Temática Digital*, 22(2), 336–353.

Gonzalez-Baixauli, C., Montañes-Brunet, E., & Pérez-Vázquez, P. J. (2018). Effects of mobility programmes on university students' academic performance. In *4th International Conference on Higher Education Advances (HEAD'18)*, Editorial Universitat Politecnica de Valencia, pp. 553–562.

González, X., & Pazó, C. (2008). Do public subsidies stimulate private R&D spending? *Research Policy*, 37(3), 371–389.

Gopalakrishnan, V., Wadhwa, D., Haddad, S., & Blake, P. (2021). *2021 Year in Review in 11 Charts: The Inequality Pandemic*. The World Bank News. Retrieved April 22, 2022, from https://www.worldbank.org/en/news/feature/2021/12/20/year-2021-in-review-the-inequality-pandemic

Granja, C. D. (2018). *Internacionalização e mobilidade estudantil: o programa Ciência sem Fronteiras na Universidade Estadual de Campinas* [Master's thesis, University of Campinas].

Granja, C. D., & Carneiro, A. M. (2020). EU-Brazil Cooperation: The Science without Borders Programme Experience. In *Building Higher Education Cooperation with the EU* (pp. 129–145). Brill Sense.

Granja, C. D., & Visentin, F. (2021). International student mobility and academic performance: Does timing matter? *Maastricht Economic and Social Research Institute on Innovation and Technology (UNU-MERIT) Working Paper*, 2021-049.

Guillaud, E. (2013). Preferences for redistribution: An empirical analysis over 33 countries. *Journal of Economic Inequality*, 11(1), 57–78.

Guo, S., & Fraser, M. W. (2015). Propensity score analysis: Statistical methods and applications. *SAGE publications*, 2nd edition.

Guruz, K. (2008). *Higher Education and International Student Mobility in the Global Knowledge Economy*. SUNY Press.

Heckman, J. J., LaLonde, R. J., & Smith, J. A. (1999). The economics and econometrics of active labor market programs, In O. Ashenfelter and D. Card (eds), *Handbook of Labor Economics*, Vol. III, pp. 1865–2097, Amsterdam: Elsevier.

Hjerm, M., & Schnabel, A. (2012). How much heterogeneity can the welfare state endure? The influence of heterogeneity on attitudes to the welfare state. *Nations and Nationalism*, 18(2), 346–369.

Jaime-Castillo, A. M., & Saez-Lozano, J. L. (2016). Preferences for tax schemes in OECD countries, self-interest and ideology. *International Political Science Review*, 37(1), 81–98.

Jaime-Castillo, A. M., Fernández, J. J., Valiente, C., & Mayrl, D. (2016). Collective religiosity and the gender gap in attitudes towards economic redistribution in 86 countries, 1990–2008. *Social science research*, 57, 17–30.

Janmaat, J. G. (2013). Subjective inequality: A review of international comparative studies on people's views about inequality. *European Journal of Sociology*, 54(3), 357–389.

Jenkins, S. P., & Van Kerm, P. (2011). The measurement of economic inequality. *The Oxford Handbook of Economic Inequality*, Oxford University Press.

Jetten, J., Peters, K., Álvarez, B., Casara, B. G. S., Dare, M., Kirkland, K., ... , & Mols, F. (2021). Consequences of economic inequality for the social and political vitality of society: A social identity analysis. *Political Psychology*, 42, 241–266.

Junor, S., & Usher, A. (2008). *Student Mobility & Credit Transfer: A National and Global Survey*. Educational Policy Institute.

Kim, H., Huh, S., Choi, S., & Lee, Y. (2017). Perceptions of inequality and attitudes towards redistribution in four East Asian welfare states. *International Journal of Social Welfare*, 27(1), 28–39.

Lépine, A., Treibich, C., & d'Exelle, B. (2020). Nothing but the truth: Consistency and efficiency of the list experiment method for the measurement of sensitive health behaviours. *Social Science & Medicine*, 266, 113326.

Leuven, E., & Sianesi, B. (2003). P*SMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing*. Retrieved August 2022, from http://ideas.repec.org/c/boc/bocode/s432001.html.

Lopes, A. D. (2020). International mobility and education inequality among Brazilian undergraduate students. *Higher Education*, pp. 1–18.

Lubker, M. (2004). Globalization and perceptions of social inequality. *International Labour Review*, 143(1-2).

Marandola, G., & Xu, Y. (2021). *(Mis-)perception of inequality: measures, determinants and consequences*. Publications Office of the European Union, https://data.europa.eu/doi/10.2760/444832

Medgyesi, M. (2013). Increasing income inequality and attitudes to inequality: a cohort perspective. *GINI Discussion Paper*, 94(January, 2013).

Meltzer, A. H., & Richard, S. F. (1981). A rational theory of the size of government. *Journal of Political Economy*, 89(5), 914–927.

Meya, J., & Suntheim, K. (2014). The second dividend of studying abroad: The impact of international student mobility on academic performance. *CEGE Discussion Papers*, 215.

Nassif Pires, L., Carvalho, L. B. D., & Lederman Rawet, E. (2021). Multi-dimensional inequality and Covid-19 in Brazil. *Investigación económica*, 80(315), 33–58.

Ohtake, F. (2008). Inequality in Japan. *Asian Economic Policy Review*, 3(1), 87–109.

Osberg, L., & Smeeding, T. (2005). *Fair inequality? An international comparison of attitudes to pay differentials*. Retrieved August 2022, from https://www.russellsage.org/sites/all/files/u4/Osberg%20&%20Smeeding.pdf

Osberg, L., & Smeeding, T. (2006). “Fair” Inequality? Attitudes toward Pay Differentials: The United States in Comparative Perspective. *American Sociological Review*, 71, 450–473.

OXFAM. (2017). *Nós e as Desigualdades: Pesquisa OXFAM Brasil/Datafolha, Percepções sobre Desigualdades no Brasil*. OXFAM Brasil, São Paulo.

Parey, M., & Waldinger, F. (2011). Studying Abroad and the Effect on International Labour Market Mobility: Evidence from the Introduction of Erasmus. *The Economic Journal*, 121(551), 194–222.

Poppitz, P. (2016). Does self-perceptions and income inequality match? The case of subjective social status, *IMK Working Paper*, 173.

Reeves, R., & Mager, F. (2018). *Attitudes Towards Inequality in the UK A review of opinion surveys*. OXFAM Research Report.

Roex, K. L., Huijts, T., & Sieben, I. (2018). Attitudes towards income inequality: ‘Winners’ versus ‘losers’ of the perceived meritocracy. *Acta Sociologica*.

Rosenbaum, P., & Rubin, D. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrica*, 70, 41–55.

Rubin, D. B. (2001). Using Propensity Scores to Help Design Observational Studies: Application to the Tobacco Litigation. *Health Services & Outcomes Research Methodology*, 2, 169–188.

Saar, E. (2008). Different cohorts and evaluation of income differences in Estonia. *International Sociology*, 23(3), 417–445.

Salário. (2022). *Cargos e Salários*. Salário. Retrieved September 14, 2022, from https://www.salario.com.br

Schwartzman, S., Silva, R. L., & Coelho, R. R. (2021). Por uma tipologia do ensino superior brasileiro: teste de conceito. *Estudos Avançados*, 35, 153–186.

Sorrenti, G. (2017). The Spanish or the German apartment? Study abroad related outcomes and its recognition by the labour market. *Economics of Education Review*, 60, 142–158.

Tsai, C. (2019). Statistical analysis of the item-count technique using Stata. *Stata Journal*, 19, 390–434.

UCRH. (2022). *Teto Salarial no âmbito da Administração Direta e Autarquias do Estado*. Unidade Central de Recursos Humanos, Secretaria de Orçamento e Gestão. Retrieved September 14, 2022, from http://www.recursoshumanos.sp.gov.br/teto_salarial.html

UNESCO. (2021). *Outbound internationally mobile students by host region*. UNESCO Institute for Statistics. Retrieved June 18, 2021, from http://data.uis.unesco.org

Wang, Z., Crawford, I. & Liu, L. (2019). Higher achievers? Mobility programmes, generic skills, and academic learning: a U.K. case study. *Intercultural Education*, 31(1).

Warburton, E. C., Bugarin, R., & Nunez, A. M. (2001). *Bridging the Gap: Academic Preparation and Postsecondary Success of First-Generation Students*. U.S. Department of Education, National Center for Education Statistics, 153.

World Bank (2019). *Gini index (World Bank estimate) – Brazil*. World Development Indicators (WDI). Retrieved June 16, 2022, from https://data.worldbank.org/indicator/SI.POV.GINI?most_recent_value_desc=true&locations=BR

Wu, A. M., & Chou, K. L. (2017). Public Attitudes towards Income Redistribution: Evidence from Hong Kong. *Social Policy and Administration*, 51(5), 738–754.

Wulfgramm, M., & Starke, P. (2016). Divided by the Market, Divided by the State: Distribution, Redistribution and Welfare Attitudes in 47 Countries. *Scandinavian Political Studies*, pp. 1–27.

Zimmermann, J., & Neyer, F. J. (2013). Do we become a different person when hitting the road? personality development of sojourners. *Journal of Personality and Social Psychology*, 105(3), 515–530, https://doi.org/10.1037/a0033019

Appendices

A. Investigation of sampling bias

Table A – Sample of exchange students versus all exchange population at UNICAMP

	(1) Sample mobile students	(2) All mobile students	t-value (1) vs. (2)
Grade admission exam (standardized)	.32459	.26718	1.33
Black, brown or indigenous	.11705	.12077	-0.28
Female	.52363	.43388	4.40***
Age when entering university	19.662	19.115	7.08***
One or more parents had access to higher education	.70738	.71134	-0.21
Public high school	.1704	.15347	1.13
Previous internal mobility experience	.17537	.1663	0.59
Course area			
Arts	.05597	.05396	0.22
Biological Sciences and Health Sciences	.12935	.09421	2.81***
Exact, Technological and Earth Sciences	.56965	.67404	-5.34***
Humanities	.24502	.17249	4.50***

Data source: Authors' estimation from administrative and survey data.
Note. *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

B. Preference and perception survey question

Table B – Preference and perception survey question

How much do you think people with the following professions earn in Brazil? And how much do you think they should earn? We know that it is difficult to make an exact calculation, but try to give an approximate value (in Brazilian reais per month, before taxes).

	How much they earn	How much they should earn
A general practitioner	List A presented as a dropdown menu	List A presented as a dropdown menu
A president of a large national company	List A presented as a dropdown menu	List A presented as a dropdown menu
A store clerk	List A presented as a dropdown menu	List A presented as a dropdown menu
An unskilled factory worker	List A presented as a dropdown menu	List A presented as a dropdown menu
A governor of a Brazilian state	List A presented as a dropdown menu	List A presented as a dropdown menu

Note. List A has the following options: Less than 1 min. wage (to R$ 1.045,00); Between 1 and 2 min. wage (R$ 1.045,00 to R$ 2.090,00); Between 2 and 3 min. wage (R$ 2.091,00 to R$ 3.135,00); Between 3 and 5 min. wage (R$ 3.136,00 to R$ 5.225,00); Between 5 and 10 min. wage (R$ 5.226,00 to R$ 10.450,00); Between 10 and 20 min. wage (R$ 10.451,00 to R$ 20.900,00); Between 20 and 50 min. wage (R$ 20.901,00 to R$ 52.250,00); More than 50 min. wage (more than R$ 52.251,00).

C. Preference for inequality alternative measure I: the World Values Survey

The first alternative measure was inspired by the World Values Survey (WVS) strategy. Based on the WVS, we asked students where they would place themselves on a scale between 1 and 7 (Table C), in which the minimum value corresponds to "incomes should be made more equal" and the maximum to "we need larger income differences as incentives for individual effort." For this measure, low values mean accepting inequality.

Table C – Inequality preference alternative measure (World Values Survey)

How would you place your views on this scale? (if your opinion falls in between both, choose a point in the middle)							
0	1	2	3	4	5	6	7
Incomes should be made more equal						We need larger income differences as incentives for individual effort	

D. Preference for inequality alternative measure II: the preferred NGO

As a second alternative measure, we listed three non-profit organizations (NGOs) operating in Brazil, including a short description of each one (Table D). Respondents were informed that the research team would donate 200 Brazilian reais (corresponding to approximately 40 US dollars) to the NGO that obtained the most votes. Students had the choice to select one (or none) of the organizations to donate to.

For this measure, we decided to use real NGOs operating in Brazil instead of listing some hypothetical organizations to increase the accuracy of our results. Studies have already acknowledged the role of monetary incentives in reducing biases in reported beliefs about economic and political facts (Bullock *et al.*, 2015; Cappelen *et al.*, 2018). Even though we did not pay respondents directly to answer this question in the survey nor ask students to donate their own money, giving respondents the option of donating real money is a transparent way of incentivizing them to inform true preferences.

Table D – Inequality preference alternative measure (preferred NGO)

Below we list three NGOs that operate in Brazil, including a short description of each one (extracted from their official sources). **SOS Amazônia** (www.sosamazonia.org.br) Mission: Promote the conservation of biodiversity and the growth of environmental awareness in the Amazon. **Abrace** (www.abrace.com.br) Mission: To permanently seek excellence in social assistance to the families of children and adolescents with cancer and blood disorders, in addition to valuing volunteers and supporters. **CENPEC** (www.cenpec.org.br) Mission: Contribute to the reduction of inequalities in the country, through the production of knowledge and impact on public policies in the field of education and in its articulation with other rights. The research team is committed to donating R$200,00 to the NGO that obtains the most votes. Which of these NGOs would you like to contribute to? ☐ SOS Amazônia ☐ Abrace ☐ CENPEC ☐ None

E. Preference for inequality alternative measure III: the double-list experiment

For our last measure of inequality preference, we decided to run a double-list experiment, a variation of the more known list-experiment (or item-count technique). We chose to include a small experiment in our survey, given that asking questions about sensitive topics (such as inequality preferences) can make respondents hesitant to report their true opinions (Glynn, 2013; Lépine *et al.*, 2020).

In this type of social experiment, respondents are randomly assigned to two groups (treatment and control) and asked how many of a list of questions apply to them without reporting which ones. The individuals in the control group are presented with a list of statements, while those in the treatment group receive the same list plus a sensitive item. Comparing the average response given by both groups provides an estimate of the prevalence of the sensitive behavior in the treatment group.

An advantage of this kind of method is that, as long as the complete list does not apply to the individual, they can be assured that their answer to the sensitive question is unknown (Glynn, 2013), reducing the level of self-disclosure that a truthful response requires (Droitcour *et al.*, 1991; Blair & Imai, 2012). Moreover, if answers are recorded across many individuals, it provides a statistically unbiased prevalence estimate for the population and its selected subgroups (Droitcour *et al.*, 1991).

To increase the efficiency of the estimators and reduce their variance, a double-list version of the list-experiment was used (Droitcour *et al.*, 1991). In this case, two lists were used instead of one, with each group serving as treated for the first experiment and control for the second or vice versa (Droitcour *et al.*, 1991; Lépine *et al.*, 2020). All respondents, regardless of group, had to provide information about the key item (Tsai, 2019), and the answers to both experiments were averaged to provide a single estimate (Droitcour *et al.*, 1991).

The statements used in the two list-experiments were presented to respondents randomly and are listed in Table E.[15]

[15] To reduce the so-called floor and ceiling effects i.e., when respondents honestly respond "no" or "yes" to all items, we included in both lists a pair of statements that are expected to be negatively correlated with each other. Floor and ceiling effects are undesirable in list-experiments since it harms respondents' confidentiality and reveal their true preferences, reducing their motivation to report an honest response to the sensitive item. In list A, it is expected that people who are agree with large corporations polluting the environment are more likely to disagree with the increase in the fossil fuel tax and vice versa. For list B, those who agree with the prohibition of same-sex marriage would be more likely to disagree with the adoption of children by a homosexual individual or by a homosexual couple and vice versa.

Table E – Inequality preference alternative measure (double-list experiment setting)

<table>
<tr><td colspan="2">Below are listed some items that sometimes make people angry or upset. After reading them, tell us HOW MANY of them upset you. We do not want to know which ones, just how many.</td></tr>
<tr><td>Group 1 – list A (control)
• Large corporations polluting the environment
• Government demanding seat belts when driving
• The increase in the fossil fuel tax

Number of agreed statements: X_{1A} (max: 3)</td><td>Group 2 – list A (treatment)
1. Large corporations polluting the environment
2. Government demanding seat belts when driving
3. The increase in the fossil fuel tax
4. <u>Income inequality in Brazil</u>

Number of agreed statements: X_{2A} (max: 4)</td></tr>
<tr><td>Group 1 – list B (treatment)
• The prohibition of same-sex marriage
• People who consume meat
• The government installing more speed cameras
• The adoption of children by a homosexual individual or by a homosexual couple
• <u>Income inequality in Brazil</u>

Number of agreed statements: X_{1B} (max: 5)</td><td>Group 2 – list B (control)
• The prohibition of same-sex marriage
• People who consume meat
• The government installing more speed cameras
• The adoption of children by a homosexual individual or by a homosexual couple

Number of agreed statements: X_{2B} (max: 4)</td></tr>
</table>

Note. Respondents assigned to Group 1 served as control units for list A and as treated for list B, while respondents assigned to Group 2 served as treated for list A and as the control for list B.

In this case, any individual in the treatment group reporting less than four items for list A (X_{2A}) or less than five items for list B (X_{1B}) could dislike income inequality in Brazil. If both groups are honest when answering the question, the randomization into control and treatment groups allows estimating the proportion of subjects involved in the sensitive behavior (p) by taking the difference between the average response among the treatment and the control groups (Equation A). In our case, our estimate reports the estimated prevalence of inequality aversion in our sample, meaning that if p is equal to 0.1, then 10% of respondents would be upset about income inequality in the country.

$$estimate\ (p) = \frac{1}{2}[(\bar{X}_{2A} - \bar{X}_{1A}) + (\bar{X}_{1B} - \bar{X}_{2B})] \qquad \text{(A)}$$

F. Preference for inequality alternative measures: average treatment effects

Table F – Average treatment effect on the treated, alternative inequality preference measures

	World Values Survey		Preferred NGO		Double list-exp.	
Preferred inequality	(I)	(II)	(I)	(II)	(I)	(II)
	.036	.035	.151	.150	.028	.019
	(.095)	(.096)	(.108)	(.108)	(.046)	(.046)
Untreated	751	751	739	739	751	751
Treated	776	776	741	741	776	776
PSM covariates	No	Yes	No	Yes	No	Yes

Data source: Authors' estimation from administrative and survey data.

Note. Average treatment effect calculated using weights based on the propensity score; standard errors in parentheses; only observations on common support are used; the variable based on the World Values Survey was estimated using an Ordered Logistic Regression; the variable about the preferred NGO was estimated using a Logistic Regression; the double-list experiment was calculated using the module kict for Stata 17 (Tsai, 2019); (I) corresponds to the model with no covariates and (II) corresponds to the regression including all matching covariates; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

G. Sensitivity to different matching algorithms/techniques

We test the robustness of our main results regarding the choice of different matching methods, comparing results from the original linear model calculated using sample weights based on the propensity score with other matching techniques such as Kernel, 5-Nearest Neighbors, and Coarsened Exact Matching.[16] Results for our two main outcome variables are presented in Table G1 and Table G2. They show that our conclusions remain the same regardless of the choice of algorithm/technique for matching.

[16] While for k-Nearest Neighbors (NN) matching, k units from the comparison group are selected as matching partners for a treated unit that has the closest propensity score, in Kernel matching the algorithm uses weighted averages of (nearly) all individuals in the control group to construct the counterfactual outcome (Caliendo & Kopeinig, 2008). Coarsened Exact Matching (CEM), on the other hand, presents an alternative to propensity score matching, which works by temporarily coarsening the data according to pre-selected variables and performing exact match on the coarsened data and then running the analysis on the uncoarsened, matched data (Blackwell *et. al,* 2009).

Table G1 – Average treatment effect on the treated, preferred inequality, alternative matching algorithms/techniques

Preferred inequality	Original model		Other matching algorithms		
	(I)	(II)	Kernel	NN(5)	CEM
	-.0037983	-.0038001	-.0047261	-.0106664	-.0032168
	(.0074413)	(.007199)	(.0078229)	(.0097758)	(.0092074)
Untreated	751	751	751	751	598
Treated	776	776	776	776	657
PSM covariates	No	Yes	No	No	No

Data source: Authors' estimation from administrative and survey data.
Note. Kernel and Nearest Neighbors (NN) estimated using the module psmatch2 for Stata 17 (Leuven & Sianesi, 2003); Kernel matching estimated with bootstrap standard errors (200 repetitions) and 0.06 bandwidth; 5-Nearest Neighbors calculated with replacement and with sample standard error (i.e., heteroskedasticity-consistent analytical standard errors); Coarsened Exact Matching coefficients calculated through a linear model using weights estimated with the module cem for Stata 17 (Blackwell *et al.*, 2009) and robust standard errors; standard errors in parentheses; (I) corresponds to the model with no covariates and (II) corresponds to the regression including all matching covariates; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

Table G2 – Average treatment effect on the treated, perceived inequality, alternative matching techniques

Perceived inequality	Original model		Other matching algorithms		
	(I)	(II)	Kernel	NN(5)	CEM
	-.0089182 ***	-.0089028 ***	-.009237 ***	-.0073090 *	-.0095596 ***
	(.0029684)	(.0029578)	(.0030636)	(.0039126)	(.0036596)
Untreated	751	751	751	751	598
Treated	776	776	776	776	657
PSM covariates	No	Yes	No	No	No

Data source: Authors' estimation from administrative and survey data.
Note. Kernel and Nearest Neighbors (NN) estimated using the module psmatch2 for Stata 17 (Leuven & Sianesi, 2003); Kernel matching estimated with bootstrap standard errors (200 repetitions) and 0.06 bandwidth; 5-Nearest Neighbors calculated with replacement and with sample standard error (i.e., heteroskedasticity-consistent analytical standard errors); Coarsened Exact Matching coefficients calculated through a linear model using weights estimated with the module cem for Stata 17 (Blackwell *et al.*, 2009) and robust standard errors; standard errors in parentheses; (I) corresponds to the model with no covariates and (II) corresponds to the regression including all matching covariates; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

H. Impact of an exchange program on students' incomes and well-being

Table H – Average treatment effect on the treated, income and well-being perception

	Current per capita income		Current well-being	
	(I)	(II)	(I)	(II)
	2.378031***	2.377722***	.6722307***	.6724732***
	(.2817712)	(.2761086)	(.0924138)	(.0875248)
Untreated	734	734	751	751
Treated	723	723	775	775
PSM covariates	No	Yes	No	Yes

Data source: Authors' estimation from administrative and survey data.

Note. Average treatment effect calculated through a linear model using weights based on the propensity score; standard errors in parentheses; only observations on common support are used; (I) corresponds to the model with no covariates and (II) corresponds to the regression including all matching covariates; *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

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2023-01 *Can international mobility shape students' attitudes toward inequality? The Brazilian case* by Cintia Denise Granja, Fabiana Visentin and Ana Maria Carneiro