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Spatial inequalities in educational opportunities: The role of public policies

Noemí Katzkowicz[1] | **Martina Querejeta**[2] | **Tatiana Rosá**[3]

[1]Instituto de Economía, FCEA, Universidad de la República and Hebrew University, Jerusalem. noma.katzkowicz@fcea.edu.uy

[2]Instituto de Economía, FCEA, Universidad de la República and PhD student, Universidad Nacional de La Plata. martinaquerejeta@gmail.com

[3]Pontificia Universidad Católica de Chile. tatiana.rosa@uc.cl

This paper documents spatial patterns in intergenerational mobility at the top of the educational distribution and assess the role of public policies in increasing educational opportunities. Our analysis relies on novel administrative data of public university students in Uruguay's, a small high income developing country. We first document that the percentage of university students whose parents did not attain university increased 7 p.p between 2002 and 2020. Tough this imply a significant increase in intergenerational mobility spatial inequality still prevails. As a way to reduce this inequality of opportunities, the main public University started a campus expansion policy in 2008. We exploit the time and location variation in the implementation to provide causal evidence of its impact on total enrollment and the share of first-generation university students (mobility at the top). Results from the difference in differences analysis show that the policy was successful in increasing the number of students from localities and the share of students with parents that do not hold a university degree (3% increase) in those localities where campuses opened but also in those 50 kms around. Our results suggest the important role of public policies in the reduction of inequality of opportunities and in increasing mobility at the top.

KEYWORDS

Intergenerational mobility, Education, Spatial inequalities, Developing countries

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Desigualdades espaciales en las oportunidades educativas: El papel de las políticas públicas

Noemí Katzkowicz[1] | **Martina Querejeta**[2] | **Tatiana Rosá**[3]

[1]Instituto de Economía, FCEA, Universidad de la República and Hebrew University, Jerusalem. noma.katzkowicz@fcea.edu.uy

[2]Instituto de Economía, FCEA, Universidad de la República y Doctorando en Economía, Universidad Nacional de La Plata. martinaquerejeta@gmail.com

[3]Pontificia Universidad Católica de Chile. tatiana.rosa@uc.cl

Este trabajo documenta los patrones espaciales de la movilidad intergeneracional en la parte superior de la distribución educativa y evalúa el papel de las políticas públicas en el aumento de las oportunidades educativas. Nuestro análisis se basa en novedosos datos administrativos de estudiantes de universidades públicas en Uruguay, un pequeño país en desarrollo de altos ingresos. En primer lugar, documentamos que el porcentaje de estudiantes universitarios cuyos padres no llegaron a la universidad aumentó 7 puntos porcentuales entre 2002 y 2020. Aunque esto implica un aumento significativo de la movilidad intergeneracional, la desigualdad espacial sigue prevaleciendo. Como forma de reducir esta desigualdad de oportunidades, la principal universidad pública inició una política de expansión del campus en 2008. Aprovechamos la variación temporal y de localización en la implementación para proporcionar evidencia causal de su impacto en la matrícula total y la proporción de estudiantes universitarios de primera generación (movilidad en la cima). Los resultados del análisis de diferencia en diferencias muestran que la política tuvo éxito al aumentar el número de estudiantes de las localidades y la proporción de estudiantes con padres que no tienen un título universitario (aumento del 3%) en las localidades donde se abrieron los campus, pero también en las que se encuentran a 50 km a la redonda. Nuestros resultados sugieren el importante papel de las políticas públicas en la reducción de la desigualdad de oportunidades y en el aumento de la movilidad en la cima.

KEYWORDS

Movilidad intergeneracional, Educación, Desigualdad espacial, Países en desarrollo

1 | INTRODUCTION

Children and parents educational attainments are highly correlated (Black et al., 2005; Black and Devereux, 2011; Björklund and Salvanes, 2011). This suggest a strong transmission of human capital between parents and offspring. However, most of the literature on intergenerational mobility focus on income mobility for developed countries. For developing countries literature is scarcer and mostly concentrated in analyzing mobility in educational attainment (Torche, 2019). Moreover, despite the empirical evidence of lower intergenerational mobility at the top of the income distribution (Corak, 2013; Spenkuch, 2015), we know little on (low) mobility at the top of the education distribution (Neidhöfer et al., 2018). In addition, while there is a vast literature documenting the spatial inequality in income intergenerational mobility (Chetty et al., 2014), little is known on the spatial distribution of educational mobility. Are people from bigger cities, with higher educational supply, more likely to move-up in the educational distribution than those from smaller cities? Is there room for public policies to modify these trends?

This paper aims to contribute by filling these research gaps. We document spatial patterns in educational mobility at the top of the distribution in Uruguay, a small high income developing country. We analyze the main trends in intergenerational mobility measured as the share of students that are the first in their families to enroll in University. Though there are a number of possible explanations behind the correlation between offspring' educational choices and parent's educational background, recent literature try to shed light on the nature(selection) versus nurture(causality) hypothesis.[1] To provide causal evidence of the nurture hypothesis, we exploit a University reform that increased the number of campuses across the country. Historically, the public University campuses were located at the country capital, and therefore, students from outside the capital had to face extra costs in order to study a University degree (e.g. moving or traveling). In 2008 a geographic expansion policy was implemented in order to decrease this cost heterogeneity. Conceptually, we can assume the educational choice depends on the cost of education, its return, and, in the case where families are credit constrained, on family income. By decreasing the cost of university education, we expect this policy not only to increase enrollment but also to increase the number of first generations students who, given their parental background, might have lower returns to education or be more financially constrained. The policy was implemented gradually in space and time given budget constraints. We exploit this variation in time and location, and estimate a staggered difference-in-difference model with fixed effects.

Our analysis uses novel administrative data of students in Uruguay's main public university –named *Universidad de la República*–, an institution in which there are no admission exams or tuition fees to enroll in. The dataset covers the period 2002 to 2020 and represents more than 86% of total tertiary students in Uruguay.[2] According to the National Household Survey, 80% of individuals that were 30 or less in 2020 had 12 or less years of education. Therefore, this study focuses on the top 20% of the years of education distribution.

The descriptive results show a significant increase in upward mobility at the top of the educational distribution. The percentage of university students whose parents did not attain university increased around 7 p.p between 2002 and 2020. Our results further show high spatial inequality in the distribution of educational opportunities across Uruguay. On the one hand, the number of students enrolled in university and the number of first generation students enrolled in university is higher in the country capital compared to all other localities. On the other hand, students from the capital city face the lowest mobility

[1] See Björklund and Salvanes (2011) and Fleury and Gilles (2018) for a review of the literature on mechanisms behind intergenerational mobility in education.

[2] The remaining 14% attend vocational training, teacher training programs or private universities (Udelar, 2020).

measured as the percentage of first generation students among total enrollment. Finally, we find that upward mobility is higher among female students compared to men (10 p.p) and that holds for all localities in the country.

Moreover, we provide robust causal evidence that the increase in upward mobility was explained to some extent by the geographical expansion policy carried out by the public University from 2008. Our results show that the policy was successful in increasing the number of students from localities where campuses opened, and increasing the share of students with parents that do not hold a university degree around 3%. That is, the policy had a positive and significant effect on increasing mobility at the top of the distribution of educational attainments. Moreover, these results also hold for localities up to 50 kms away from where the new campuses opened. These results also arises when analyzing the probability that a student who enrolled in university have parents that do not hold a university degree. Specifically, the opening of a new campus in a given locality implied: an average increase of 66 new students enrolling in university coming from that locality, and a 3% average increase in the share of students with non university graduate parents, all compared to those localities where no campus opened.

This paper contributes to two strands of the literature. Firstly, to the literature on intergenerational transmission of education in developing countries. Despite the vast empirical literature on income mobility in developed countries (Black and Devereux, 2011; Chetty et al., 2014; Jäntti and Jenkins, 2015; Chetty et al., 2020) and a growing one for developing countries (Cuesta et al., 2011; Ferreira et al., 2013), relative less work has focused on education as the variable of interest (Black et al., 2005; Björklund and Salvanes, 2011; Daude and Robano, 2015; Fleury and Gilles, 2018; Björklund and Jäntti, 2020), specially when it comes to developing countries (see Torche (2019) for a review). Neidhöfer et al. (2018) find that intergenerational educational mobility is rising in Latin America and document substantial immobility at the top of the distribution. We take advantage of a novel dataset such as administrative records of university students and contribute to this literature by shedding light on mobility at the top of the educational distribution. We also find low mobility at the top adding spatial and gender dimensions. While there is high spatial inequality in this low intergenerational mobility, we find no evidence of gender patterns. Previous literature on intergenerational mobility in Uruguay provides evidence on income mobility (Leites et al., 2020; Araya, 2019), years of education (Soto, 2020; Robano, 2012; Sanroman, 2010) and occupations (Urraburu, 2020), but there is no evidence focusing on the top of the educational distribution. Also this literature does not analyze the spatial dimension of mobility.

Secondly, this papers also relates to the literature on the role of public policies in increasing intergenerational mobility in developing countries. We take advantage of the public university spatial expansion policy to provide causal evidence on the effects of building infrastructure and invest in public university in educational mobility.[3] Consistent with Duflo (2001) we find that public investment in infrastructure increases human capital (number of university students). Furthermore, we also find an increase in intergenerational mobility of education (the share of students with non university parents), and a reduction of spatial inequality in intergenerational mobility, consistent with Meneses et al. (2021).

The rest of the paper proceeds as follows. Section 2 describes the relevant institutional context including details on the university spatial expansion policy. Section 3 presents our empirical framework to analyze human capital transmission and intergenerational mobility in education, including our empirical measure for upward mobility at the top of

[3] Méndez (2020) analyze the same policy and finds that university enrollment increases explained mostly by students from high-educational background. However, the evidence is not causal and do not address the gender dimension neither intergenerational mobility.

the education distribution. In Section 4 we describe our dataset and sample selection, and specify the data limitations that drove our empirical analysis. Intergenerational mobility is documented in Section 5. The identification strategy is presented in 6 and in Section 7 we show the main results of evaluating the university spatial expansion. Finally, Section 8 concludes.

2 | INSTITUTIONAL CONTEXT

Uruguay is a Latin American developing country with around 3.5 million inhabitants. It is one of the countries with higher GDP per capita[4] and lower income inequality in the region. It is also well known for having a strong welfare state providing, among others, public education with free access at all levels. The public educational system is wide and there are no access restrictions. In particular, Uruguay's public University has no admission exams or tuition fees, easing access for whoever interested. Yet, completion rates of secondary school and enrollment in tertiary education are low.

Educational coverage at mandatory levels in Uruguay increased substantially in the last decade.[5] Nevertheless, while coverage is almost universal until 14 years of age, educational attainment significantly drops in upper secondary school (ages 15 to 17). Moreover, strong socioeconomic patterns still prevail and girls and boys from lower income backgrounds face lower educational attainment in almost all levels (INEEd, 2018).[6] Therefore, while from preschool until lower secondary school Uruguay is well positioned in the Latin American context, secondary school completion is a concerning challenge for policy makers. This gauge is around 40% for people aged between 20 to 24, well below the Latin American average (62%) (INEEd, 2020). As a consequence, attendance at tertiary level is still low and around 26% of the population between 25 and 29 years of age attend University with a strong socioeconomic gradient (Udelar, 2020). This is relatively low for a country that has a free-of-charge educational system.

Geographically Uruguay is divided in 19 divisions called departments and each department subdivided in several locations. The capital of the country is Montevideo and concentrates almost half of the population. As it is usual in most countries, majority of services and public buildings are also concentrated in the capital city. In particular, Uruguay's main public University -named *Universidad de la República*- was historically mainly located in Montevideo.

This University covers more than 86% of total tertiary students.[7] However, the location at the capital city implied that students from outside Montevideo had to face extra costs in order to study a University degree (e.g. moving or travelling). In 2008 a decentralization policy was implemented in order to decrease this cost heterogeneity. The policy was implemented gradually in space and time. Before 2008, three departments already had campuses but the university reform substantially increased the number of degrees offered, their budget and infrastructure over the period. By 2020, seven out of the nineteen departments had University's campuses. Figure 1 shows the timing of University expansion.

[4] Uruguay's GDP ranked in the top 3 within Latin American countries, depending on the year, according to World Bank Statistics

[5] Particularly, secondary completion rates increased almost 10 pp since 2006 as shown in Panel (b) of Figure A.1

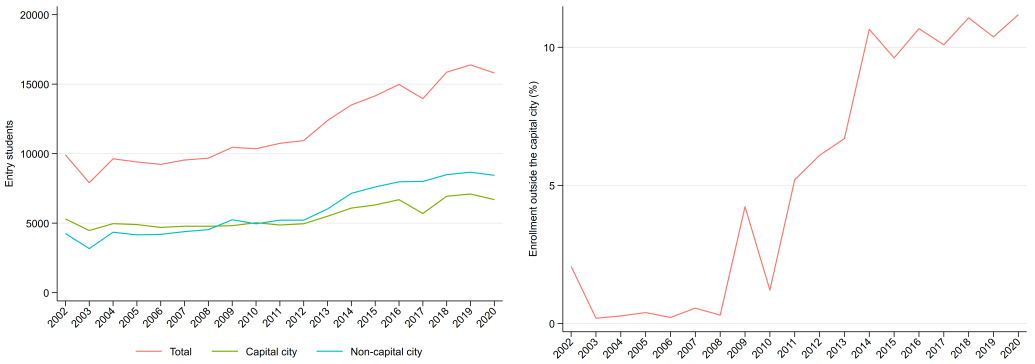
[6] See Panel (a) of Figure A.1

[7] The remaining 14% attend vocational training, teacher training programs or private universities (Udelar, 2020).

Before 2008	2008	2010	2012	2013	2014	2019
Paysandu*	Paysandu*	Paysandu*	Paysandu*	Paysandu*	Paysandu	Paysandu
Rivera*	Rivera*	Rivera*	Rivera*	Rivera	Rivera	Rivera
Salto*	Salto*	Salto*	Salto*	Salto*	Salto	Salto
	Maldonado	Maldonado	Maldonado	Maldonado	Maldonado	Maldonado
	Rocha	Rocha	Rocha	Rocha	Rocha	Rocha
	Treinta y Tres*	Treinta y Tres*	Treinta y Tres*	Treinta y Tres*	Treinta y Tres*	Treinta y Tres*
			Tacuarembo	Tacuarembo	Tacuarembo	Tacuarembo

FIGURE 1 University expansion.
Notes: Own elaboration based on University official documents. Unless specified, campuses are located at the capital of the department. * Indicates that a university center is open but with highly limited educational offer. When removed, indicates that a bigger campus was open.

The geographical expansion was followed by an increase in enrollment of students living outside Montevideo. Panel (a) in Figure 2 shows the evolution over time of the number of entry students by geographical region where living prior to entering University. In 2002, students from outside the capital represented 44.5% of total enrollment, while in 2020 this gauge increased to 58%. Moreover, the decentralization policy was effective in reducing the migration of University students from their home-locality to the capital city. Panel (b) in Figure 2 shows the share of entry students by geographical region where studying the first year at University. The people enrolled at a University campus outside the capital city increased from around 0.2% to 10% in the analyzed period.



(a) Region of origin (b) Region of destination

FIGURE 2 Entry students by geographical region of origin and destination, years 2002-2020.
Notes: The figure in Panel (a) shows the number of entry students by region where living prior to entering University. The figure in Panel (b) shows the share of entry students enrolled in a University Campus outside the Capital city. All new entry students with information both in administrative records and the census in the enrollment year were considered. Sample drawn from UdelaR administrative records and Census at enrollment year.

3 | EMPIRICAL FRAMEWORK

Parents transmit human capital to their children. Human capital is a summary measure of resources, norms, and ability, which contributes to educational attainment. Nature or nurture, there are a number of possible explanations behind this transmission. Ideally, we would like to observe how much of human capital is indeed transmitted from parents to children to be able to asses the heterogeneous initial conditions of children from households

with different backgrounds face. Nevertheless, human capital is unobserved. Literature on human capital has relied on educational attainment as the observed proxy for it. In other words, education and human capital are highly related, but educational attainment involves some information loss. More formally, we can assume human capital is a continues latent variable, and educational attainment a discrete observable variable, as somehow suggested by Fletcher and Han (2019). Then, one could relate the unobserved distribution of human capital and the observed one of education attainment as in Figure 3.

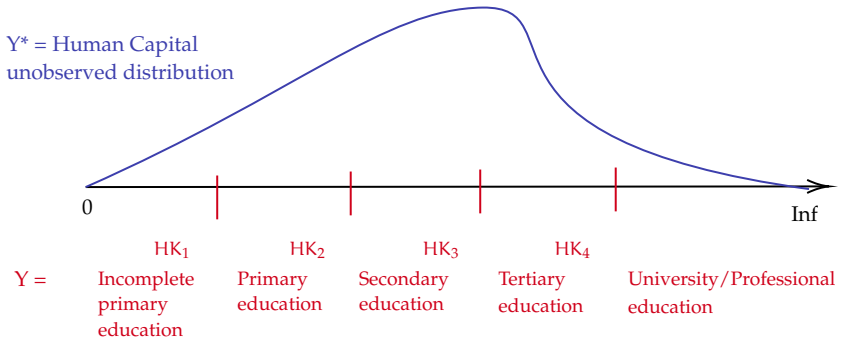


FIGURE 3 Graphic example of unobserved human capital latent distribution and educational attainment.

We then rely on this conceptual framework to relate human capital to educational attainment, and thereafter, focus on the intergenerational mobility in educational attainment.

The categorical nature of our educational outcome variables adds another limitation to our empirical study, in this case related to estimation. Several of the statistics used in the intergenerational income mobility literature would not be possible to estimate with categorical variables. Ideally, we would like to estimate children's education as a function F of their parents' education and a set of θ parameters. That is,

$$\textit{Educational Outcome Child}_i = F(\textit{Educational Outcome Parents}_i, X_i, \theta)$$

where $\textit{Educational Outcome Child}_i$ is the educational outcome of individual i, $\textit{Educational Outcome Parents}_i$ the educational outcome of the individual i' parents, and X_i a set of control variables to account for other characteristics and unobserved heterogeneity at the corresponding data level. Depending on the chosen F, the previous equation can deliver different statistics to measure intergenerational mobility. Following the prior literature on income mobility (e.g., Solon (1992)) one could estimate the log-log version and get an Intergenerational Elasticity of Human Capital, or the rank-rank regressions as in Chetty et al. (2014). Nevertheless, given that we can not observe a continues measure of $\mathtt{EducationalOutcome}$ but its discrete version (education attainment), those statistics become very hard to compute.

Given those limitations, the data restrictions, and that our goal is to study mobility at the top of the educational distribution, we propose a new statistic to measure intergenerational mobility in education. We use the percentage of students that are the first ones in their family to enroll in University with respect to the total number of enrolled students in a given year. We distinguish between: (i) students from households in which any parent ever enrolled in University, and (ii) students from households in which any parent ever enrolled in university or vocational programs .[8] We therefore define two different Statistics(

[8]We considered parents enrollment in University or vocational programs irrespectively of completion.

Equations 1 and 2) to account for this difference in parental background. Formally,

$$\textit{Perc. First generation students}_t^{UNI} = \frac{\textit{N. of enrolled students with non university parents}_t}{\textit{Number of students enrolled in university}_t} \quad (1)$$

$$\textit{Perc. First generation students}_t^{TER} = \frac{\textit{N. of enrolled students with non tertiary parents}_t}{\textit{Number of students enrolled in university}_t} \quad (2)$$

where t stands for the year of university enrollment. *Perc. First-generation students*^{UNI} considers as first-generation university students those whose parents never enrolled in university but might hold a vocational degree. When using this definition to measure intergenerational mobility we are implicitly assuming that university education, even if not completed, is upper in the educational ladder than vocational training. Measuring mobility in this way might result in changes in educational mobility even when there is no increase in the number of years of education between parents and their offspring. This assumption is based on the fact that, in Uruguay, people enrolling in university have on average higher salaries that those enrolled in vocational training, and therefore mobility measure this way might reflect income intergenerational mobility. According to Uruguay's National Household Survey, individuals between 24 to 55 years old with at least 1 year of University education, earn on average 17% more than people with vocational (non-university) education.

As a second definition of first-generation university student, we also consider those students whose parents did not attained tertiary education (*Perc. First-generation students*^{TER}). This definition does not consider as first-generation a student whose father or mother hold a vocational degree even if she is the first one in her family to ever enroll in university. On the other hand, an increase in this indicator always implies an increase in the number of years of education between parents and their offspring. Since both statistics provide different information on intergenerational mobility in education our analysis relies on both. Hereafter we will refer to the first definition of first-generation student as *first-generation with non university parents* and to the second one as *first-generation with non university nor vocational education parents*

We also compute these statistics by geographical region and gender to document heterogeneities in both dimensions. As explained before, parents educational level is computed considering the maximum level of education of both father and mother.

Though these statistics have several obvious limitations for the long run analysis, they can still be informative for the short term analysis of upward intergenerational mobility. As long as the same individual is not considered as a child and as a parent during the time span of the analysis, these gauges will give us information on the upward mobility in the right tail of the latent human capital distribution. It should be borne in mind that downward mobility would not be capture by any of those statistics. That is, if a parent holding a university degree has a child that do not enroll in University, and then according to our framework human capital would be destroyed from one generation to another, this will not be capture by any of our statistic.

Despite it limitations, a similar statistic was found to be key in efforts to widen university participation. Adamecz-Völgyi et al. (2020) analyze a wide set of socioeconomic indicators used as measures of university enrollment diversity in England. The authors find that being first-generation in family is an important barrier to university participation and provides information over and above other sources of disadvantage.

Finally, the level of persistence in socioeconomic status between one generation and

the other is usually measured in terms of relative and absolute intergenerational mobility (Chetty et al., 2014; Jäntti and Jenkins, 2015). Relative mobility measures the positional change of the offspring's in the distribution of the outcome of interest compared to their parents position. Absolute mobility measures the propensity of offspring's to gain higher achievements in the outcome of interest compared to their parents. Our proposed statistics can be considered as part of the family of those measuring absolute intergenerational mobility.

4 | DATA AND ESTIMATION SAMPLE

4.1 | Sources of information

To conduct our study we rely on administrative records of students enrolled at Uruguay's public University from 2002 to 2020. Our dataset consists of a combination of administrative records for entry students and census data applied to all students during the entry year on a mandatory basis.

Variables in the dataset include demographic and socioeconomic information on the enrolled students, including: individual characteristics, name of the center in which they completed the last year of secondary education, chosen degree, and maximum educational level attained by their parents. Using the available data we were able to recover extra information on student location prior to enter University. We implement an algorithm that extracts geographical information from the name of the center in which the student completed its last year of secondary education.[9] We were able to recover this information for more than 80% of the original sample.

4.2 | Estimation sample

For estimation purposes, we focus at individuals aged 30 or less when entering University. We also restrict the dataset to individuals that completed both administrative records and census in the enrollment year. Additionally, the sample considers only those students for which we were able to recover their location prior to enroll in university. The estimation sample consist of 168,921 students.

Table 1 provides a summary of the main variables. 61% of total entry students are female and the average age at enrollment is 19 years old. 94% of students are single and only 2% already had a child at the time of enrollment in University. The main variable under analysis is parent's level of education. 31% of total entry students have fathers with tertiary education and 23% with University level. This figures are higher when considering mothers, with 41% with tertiary education and 26% University level. Considering the maximum level of education of both father and mother, we find that 34% of total entry students comes from households with University education (completed or uncompleted).[10] Regarding the geographical dimension, it is worth noting that students from outside the capital city come from households with worse educational background: only 19% has least one parent with University educational level.

[9] See Section A.1 in the Appendix for more details on how the algorithm works.

[10] There are 6,316 students with missing information in father's level of education and 911 in mother's. For those, the maximum level of the non-missing parent was considered for computing household's educational background. There are no students with missing information in both father's and mother's education.

TABLE 1 Descriptive statistics, total and non-capital city students

	Total			Non-capital		
	Mean	SD	Obs.	Mean	SD	Obs.
Demographic characteristics						
Female	0.61	0.49	168921	0.63	0.48	74696
Age	19.31	2.61	168921	19.05	2.34	74696
Single	0.94	0.24	168914	0.94	0.24	74695
Has child	0.02	0.15	168705	0.02	0.15	74623
Parents' education						
Father primary	0.17	0.38	161108	0.25	0.43	70478
Father secondary	0.52	0.50	161108	0.55	0.50	70478
Father tertiary	0.31	0.46	161108	0.20	0.40	70478
Father University	0.23	0.42	162556	0.12	0.32	71382
Mother primary	0.14	0.34	167323	0.20	0.40	73933
Mother secondary	0.45	0.50	167323	0.50	0.50	73933
Mother tertiary	0.41	0.49	167323	0.30	0.46	73933
Mother University	0.26	0.44	168008	0.13	0.34	74309
Parent(s) University	0.34	0.47	168921	0.19	0.39	74696
Observations	168921			74696		

Notes: The table present the means, standard deviations, and number of valid observations of the main characteristics for total entry students and students from outside the capital city. The final dataset is composed of students with information both in administrative records and the census in the enrollment year, aged 30 or less when entering University and with valid geographical information. Sample drawn from UdelaR administrative records and Census at enrollment year.

5 | INTERGENERATIONAL MOBILITY IN EDUCATION

In this section, we document and analyze intergenerational mobility at the top of the educational distribution in Uruguay based on our dataset. To that end we compute the percentage of first-generation students as detailed in Section 3.[11] We analyze spatial patterns across Uruguay's localities and document heterogeneities by gender and parents' educational background between 2002 and 2020.

5.1 | Time trends in upward mobility

First, we document the evolution over time of the educational mobility measures. The percentage of first-generation students with parents with no university or vocational education is 55.3% on average for the whole sample time span. That is, more than half of new students are the first in their families in accessing tertiary educational level. Still, this means that 45% of university students come from families in which at least one parent accessed tertiary education. This is consistent with previous evidence showing high persistence at the top of years of education's distribution (Neidhöfer et al., 2018). When considering as

[11] Despite being usual in the intergenerational mobility literature to use the birth cohort as a reference, we rely on calendar years due to data representativeness. Our dataset is representative of students enrolling in each calendar year and not necessary of birth cohorts.

first-generation students those whose parents did not enroll in university, our indicator increases to 68.7% on average. Apart from the difference in their magnitudes, our statistics show very different dynamics. On the one hand, the share of first-generation students considering parents with non tertiary education is quite stable during the analyzed period. Recall that this indicator tell us about mobility in the number of years of education, therefore, this results implies that there might by no intergenerational mobility in the number of years of education in Uruguay during the analyzed period. This is consistent with the stagnation in educational mobility experienced by Uruguay that was exceptional in the Latin American context (Neidhöfer et al., 2018). On the other hand, the percentage of first-generation students when considering students whose parent did not enroll in University increased substantially during the analyzed period (7 p.p), reaching 74% in 2020. While less informative about mobility in years of education, this last measure provide evidence on substantial qualitative changes in students composition. Considering that University degrees are better paid than tertiary-non-university ones[12], this trend could imply an improvement in income mobility in the future.

FIGURE 4 Percentage of first generation students, years 2002-2020.

Notes: The figure shows the percentage of entry students that are first in their families in enrolling at tertiary level or entering University. All new entry students with information both in administrative records and the census in the enrollment year were considered. Sample drawn from UdelaR administrative records and Census at enrollment year.

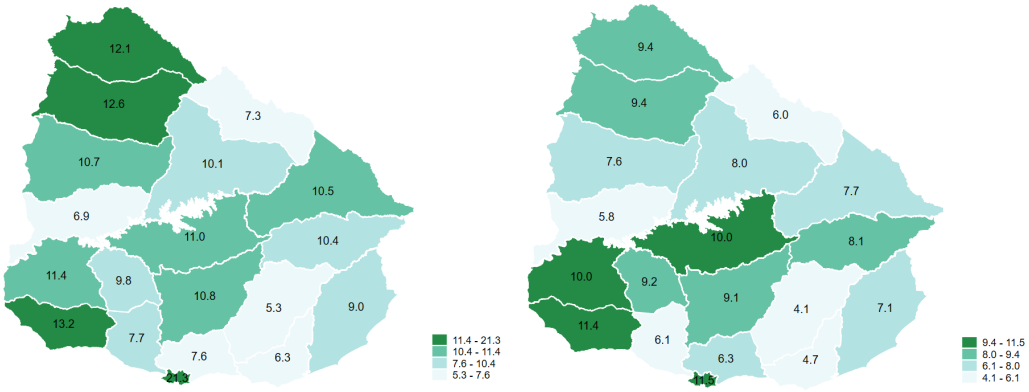
5.2 | The spatial dimension of educational mobility

Figures 5 and 6 add a spatial dimension to our analysis. First, Figure 5 documents the high spatial inequality in the distribution of university students (enrollment) and first generations students across Uruguay. Panel (a) shows the average number of students enrolled in university per 1,000 inhabitants, over all localities in each geographic department at the beginning of our study period (2002). Panel (b) shows the average number of first-generation students enrolled in university per 1,000 inhabitants, over all localities in each

[12] According to NHS individuals between 24 to 55 years old with University level, earn 17% more than people with tertiary (non-university) level.

geographic department at the beginning of our study period (2002).[13] While in the country capital there are around 20 students (per 1,000 inhabitants) enrolling in university per year, in several other departments this gauge is around 10. Panel (b) shows that while in Montevideo there are almost twelve first-generation students every 1,000 inhabitants per year, in localities in Maldonado, Lavalleja, Rivera and Rio Negro there is, on average, less than six first-generation students per year per 1,000 inhabitants.

Though educational opportunities are very unequal across Uruguayan's localities, intergenerational mobility is also highly heterogeneous across localities, but on the opposite direction. Figure 6 shows that students from the capital city face, on average, the lowest mobility regardless of their gender. It should be borne in mind that in 2002 most of university graduates lived in the capital city (80%)[14], making it more likely that a student enrolled in university coming from a locality outside the capital city to be a first-generation.



(a) Number of enrolled students (b) Number of first-generation students

FIGURE 5 Total enrollment and first-generation students per 1,000 inhabitants, in 2002.

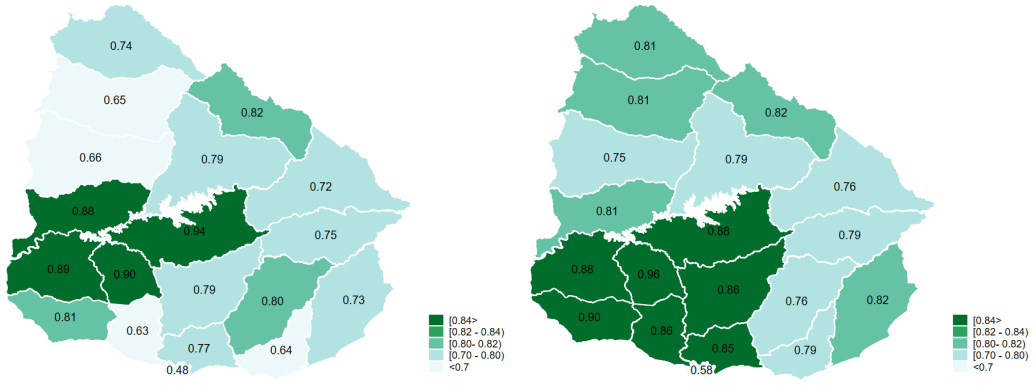
Notes: The figures show the number of enrolled students and first-generation students in 2002. Only students with information both in administrative records and the census in the enrollment year, aged 30 or less when entering University and with valid geographical information are considered in theses averages.

The analysis of gender patterns in upward educational mobility during 2002–2020 shows that upward mobility is higher and statistically significant for female students. While considering the beginning of the sample period (year 2002) 57% of male entry students are first generation in university, for women this gauge is 67%.[15] Moreover, Figure 6 shows that this result holds across all geographical regions. Literature is not conclusive regarding gender patterns of education mobility. Consistent with Leone (2021), our paper sheds light on gender patterns in intergenerational mobility and shows that persistence in education is lower for daughters than for sons.

[13] Based on population projections by the National Institute of Statistics.

[14] Data drawn from 2002's National Household Survey computed as the percentage of total people aged 30 or over with at least 1 year of University education, that live in the capital city - Montevideo. This gauge was 68% in 2019.

[15] Confidence intervals at 5% go from 0.552 to 0.589 for men and from 0.656 to 0.682 for women.



(a) Male students (b) Female students

FIGURE 6 Education inequality atlas for Uruguay by gender, year 2002.

Notes: The maps show the percentage of first generation university students by geographical region and student's sex. The dataset is composed of students with information both in administrative records and the census in the enrollment year, aged 30 or less when entering University and with valid geographical information. Sample drawn from UdelaR administrative records and Census at enrollment year.

Tough it was the high spatial inequality in educational opportunities shown in figure 5 that motivated the public university to implement the campus geographic expansion policy, in this paper we analyze if such policies also have an effect on intergenerational mobility beyond its effect on the level of university enrollment.

6 | EMPIRICAL STRATEGY

6.1 | Methodology

To identify the effect of university campus expansion policy on upward intergenerational mobility we use a staggered DiD strategy that leverages the variation in treatment time and across locations.[16] Given that we observe individual's decision but the policy varies at a locality level, we run our analyses at those two different aggregation levels: individuals and localities. While the analysis at individual level allows us to estimate changes in the probabilities of a student to be first generation conditional on being enrolled at university, aggregating the data by locality allows us to estimate the average effect of the policy on the share of students whose parents do not hold a university degree in that locality. Our empirical strategy implies that each locality l at time t is part of one of the following 3 groups: (i) untreated, if no new campuses ever opened in that locality; (ii) treated before treatment, localities that have not yet been treated (no campus opened) but eventually will; and (iii) treated after treatment, localities where new campuses already opened. Individual i is classified in the same groups according to the locality they were living before enrolling in university. Since we only observe individuals once, each of them is going to be in only one group. This is not the case when we aggregate data at a locality level. The control group will be formed by untreated and treated individuals (localities) before treatment. Our identification assumption is that, conditional on locality and calendar year fixed effects, campus openings happen as good as random.

[16] see Goodman-Bacon (2021) for a review on difference-in-differences with variation in treatment timing

Formally, we estimate the following two way fixed effect difference-in-difference models at a locality-year of enrollment and individual-locality-year of enrollment level, respectively:

$$\textit{First generation}_{i,l,t}^{Parents} = \alpha_0^i + \mu_l^i + \mu_t^i + \gamma^i T_{l,t} + \beta' X_{i,l,t} + \epsilon_{i,l,t}^i \tag{3}$$

$$\frac{\sum_{i \in l} \textit{First generation}_{i,l,t}^{Parents}}{N_{l,t}} = \alpha_0^l + \mu_l^l + \mu_t^l + \gamma^l T_{l,t} + \epsilon_{l,t}^l \tag{4}$$

where $Firstgeneration_{i,l,t}^{Parents}$ is a dummy variable that takes value 1 if student i, who lived in location l prior to enrolling in University at year t, is the first one in her family to enroll in university, and $N_{l,t}$ the total number of students coming from locality l and enrolled in University at year t. The upper scrip $Parents$ in the dependent variables distinguishes between our two measures: the one considering only students whose parents never enrolled in university ($Parents = Non - Un$) and the one considering students whose parents never attained tertiary education ($Parents = Non - Ter$) . The set of parameters μ_l and μ_t control for unobserved heterogeneity at location and year of enrollment. It should be borne in mind that our dataset is a pooled cross section of individuals, and therefore, we cannot control for students unobserved heterogeneity. $X_{i,l,t}$ is a set of control variables that includes gender and age at enrollment fixed effects. The latter is included to control for common unobserved characteristics of students belonging to the same birth cohort. Finally, the treatment variable $T_{l,t}$ indicates if a new campus has opened in location l at time t. Then γ^i and γ^l are the standard two way fixed effect difference-in-difference coefficient. While γ^i shows the effect of the policy on the probability of a student being first generation conditionally on being enrolled at university, γ^l is the effect of the policy on the share of first generation students in that locality.

Secondly, to asses the effect of the policy on total enrollment, we estimate the following two way fixed effect difference-in-difference models at a locality-year of enrollment level,

$$N_{l,t} = \alpha_0^N + \mu_l^N + \mu_t^N + \gamma^N T_{l,t} + \epsilon_{l,t}^N \tag{5}$$

where variables are defined as in Equation 4. The N superscript in the parameters makes reference to the equation we are estimating. Then, γ^N shows the effect of the policy on general enrollment.

As with many public policies, there is variability in students' adherence to the reform within treated localities. In our empirical analysis a individual is considered as affected by the program if, prior to enrolling at university, the student lived in a location where a new campus opened. We are therefore identifying and Intention to Treat effect (ITT). The ITT can be think as a lower bound in the scope of the results.

6.2 | Defining treatment

The campus expansion policy was designed to increase the supply of university degrees all over the country. Nevertheless, the intensity of that increase was not homogeneous across new campuses as explained in Section 2. Particularly, some locations already have small campuses prior to the policy implementation but there was a substantial increase in

infrastructure (new campuses opened) and resources as a result of the policy.[17] Therefore, we consider two possible scenarios. The first one in which these localities start to be treated when the new campuses opened. The second and more conservative one in which these localities have always being treated, given that there were already some campuses functioning when our sample period starts.

While campuses open their headquarters in a given location, students from close locations can be also considered as affected by the policy. Thus, alternatively we use georeferenced data and calculate the geodetic distance between each locality in a given department and the closest new campus.[18] We then define 3 buffers centered at the locality where the new campus opened with a radio of 20, 30 and 50 kilometers, respectively.[19] The new treatment variables takes value one if a new campus opened at 20, 30 of 50 kms around a given locality. Hereafter we refer to this as *Buffers*.

Our empirical strategy considers never treated localities as part of the control group. The only two exceptions are the capital of the country -Montevideo- where the University was traditionally located and the main bordering department -Canelones-. The capital is also the richest city in the country and the one with higher number of university graduates. Canelones has very good transport connections to the capital, becoming home of several individuals working in Montevideo. All those characteristics make localities in those departments structurally different from the other ones all over the country. That is why in our main analysis localities in Montevideo and Canelones are excluded from the sample. Results relaxing this assumption can be found in the Annex.

We therefore conduct our analysis under four different scenarios. Our first and baseline scenario consider as treated those students coming from locations where new campuses opened according to the timeline in Figure 1. The second, third and four scenario relies on the distance from the locality to the new campus, considering buffers of 20, 30 and 50 kms to define treatment, respectively.Other robustness on treated localities and the timeline can be found in the appendix.

6.3 | Graphic evidence

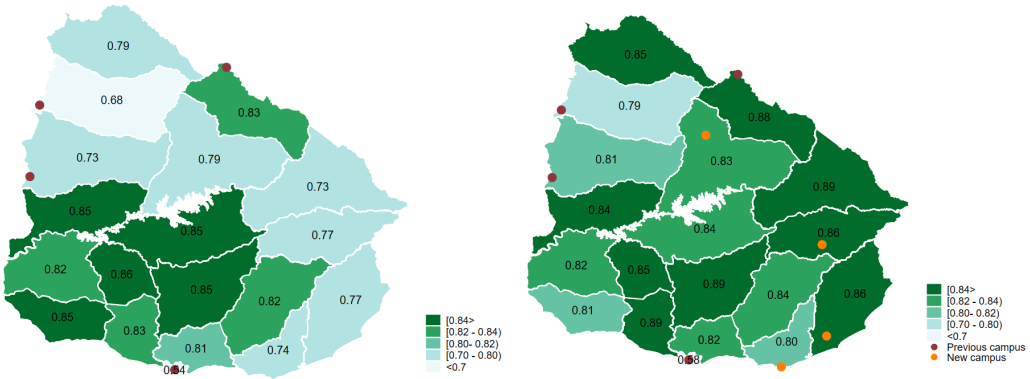
We start by presenting evidence on the evolution of vertical intergenerational mobility from a spatial perspective. Panel (a) in Figure 7 shows the average percentage of students that are the first ones in their families to enroll in university with respect to total enrollment for the period 2002-2006, and the University campuses already functioning. Panel (b) shows the average for the period 2016-2020 and the new campuses opened since 2008.[20] The average increase in the percentage of first generation in University is highly heterogeneous by geographical region. In particular, regions that opened new campuses due to University expansion policy the percentage increased on average 7pp. Meanwhile in regions with no campuses the percentage of first-generations increased by only 3pp.

[17] That is the case of Salto, Paysandu and Rivera.

[18] Geodetic distance is the length of the shortest curve between two points along the surface of a mathematical model of the earth. To calculate it we relied on the *geodist* stata command and latitude and longitude information on each locality and campus

[19] We are also working on considering roads and time travel as other measures of distances.

[20] We represent the five-year average to reduce sensibility in case of atypical years.



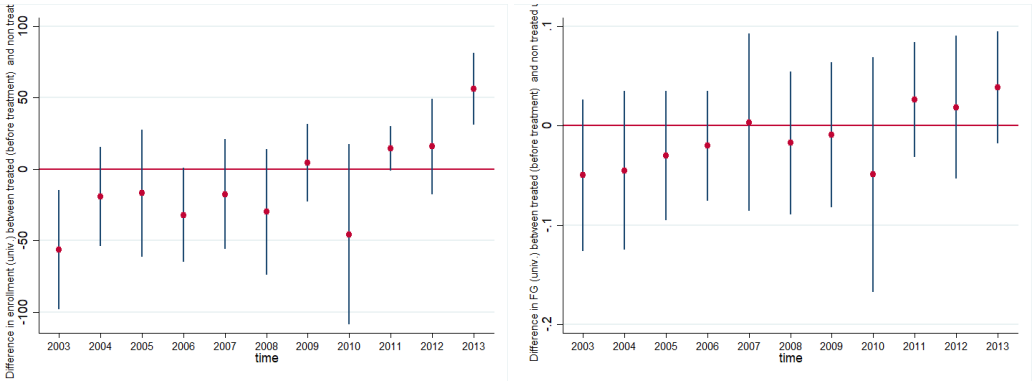
(a) 2002-2006 (b) 2016-2020

FIGURE 7 Education inequality atlas for Uruguay. Percentage of first generation university students by geographical region.

Notes: Points represent exact geographic information where University campuses are located. Previous campuses already open in 2006 in maroon and new campuses opened from 2008 onward in orange. The dataset is composed of students with information both in administrative records and the census in the enrollment year, aged 30 or less when entering University and with valid geographical information. Sample drawn from UdelaR administrative records and Census at enrollment year.

6.4 | The parallel trends assumption

As it is usual when relying in a DiD analysis, we check the comparability between control and treatment groups. Ideally we would check for: (i) the presence of common trends in both groups prior to intervention; (ii) no changes in control variables in the treatment and control group before and after the policy (composition effect). The main problem when relying in a two way fixed effect diffence-in difference approach is that there are no such pre and post intervention period for non treated units. Following Callaway and Sant'Anna (2020) we look at: (1) conditional parallel trends based on a "Never-Treated" Group, and (2) conditional parallel trends based on "Not-Yet-Treated" groups.

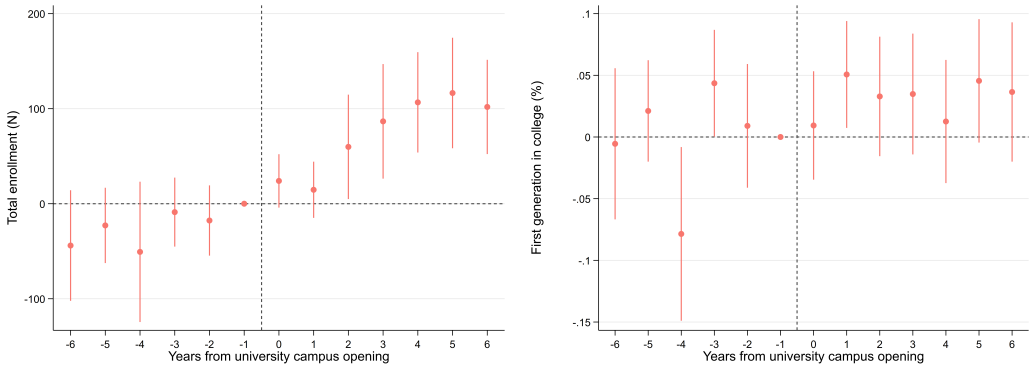


(a) Total enrollment

(b) Share of first-generation students with non-university parents

FIGURE 8 Differences in outcomes between treated localities before treatment and never treated ones.

Notes: Bandwidths represent 95% confidence intervals. Localities in the country capital (Montevideo) and in its closest department (Canelones) are not considered as part of the never treated units. The latest locality to be treated in scenario 1 are Salto and Paysandu in 2014. Averages are computed conditional on locality and calendar year fixed effects. Standard errors clustered at locality level.



(a) Total enrollment

(b) Share of first-generation students with non-university parents

FIGURE 9 Differences in outcomes between treated localities and not-yet-treated.

Notes: Bandwidths represent 95% confidence intervals. Localities in the country capital (Montevideo) and in its closest department (Canelones) are not considered. The first locality to be treated in scenario 1 is Maldonado in 2008 and the latest ones are Salto y Paysandu in 2014. Averages are computed conditional on locality fixed effects. Standard errors clustered at locality level.

7 | RESULTS

In this Section we present our main results. We run our analysis at and individual and locality level, for our three dependent variables, (i) the total number of enrolled students, (ii) the share of first-generation considering those students whose parents did not enroll in university, and (iii) the share of first-generation considering those students whose parents did not have any year of tertiary education.

7.1 | Results at locality level

Table 2 shows the estimates of equation 4 and 5. Column (1) considers treatment as detailed in Section 2, Column (2) treats localities in a radio of 20 kms as treated, and Column (3) treats localities in a radio of 30 kms as treated, and Column (4) treats localities in a radio of 350 kms as treated Estimates of γ^{NU} show the causal effect of the policy on the share of first-generation considering those students whose parents did not enroll in university,γ^{NT} the share of first-generation considering those students whose parents did not have any year of tertiary education, and γ^{N} the effect of the policy on total enrollment.

TABLE 2 Effects of the policy on the percentage of first generations students on total students at locality level.

	Baseline	Buffer 20 kms	Buffer 30 kms	Buffer 50 kms
	(1)	(2)	(3)	(4)
First generation^{NU} ($\hat{\gamma}^{NU}$)	0.050***	0.035*	0.031**	0.025
	(0.013)	(0.019)	(0.016)	(0.016)
First generation^{NT} ($\hat{\gamma}^{NT}$)	0.053***	0.027	0.030	0.023
	(0.016)	(0.026)	(0.021)	(0.022)
Total Students ($\hat{\gamma}^{N}$)	100.11***	79.39***	57.11***	41.87***
	(22.61)	(21.86)	(19.79)	(17.68)
N	981	981	981	981
Avg. enrollment before treatment	117	99	81	65

Notes: Standard errors clustered at locality level in parentheses. All specifications include calendar year and locality fixed effects. Baseline scenario considers a locality as treated according to timeline. The final dataset is composed of students with information both in administrative records and the census in the enrollment year, aged 30 or less when entering University and with valid geographical information. Montevideo and Canelones are excluded. Sample drawn from UdelaR administrative records and Census at enrollment year. ***significant at the 1% level, **5% level, *10% level.

First and second row of Column (1) reports an increase of 5.0% and 5.3% in the share of first generation students coming from localities in which new campuses opened compared to those localities in which they did not, using our two measures of mobility. Those estimates suggests a positive and significant increase in educational mobility as a result of the policy. The effect decrease in intensity as we increase the distance to where the new campus opened. For the share of first-generation whose parent did not enroll in university, there is an increase of around 3% for those localities 20 kms (Colum(2)) and 30 kms away(Colum(3)), statistically significant at 10% and 5% level, respectively. The effect vanishes for students living 50 kms from the new campus. For the case of first-generation students whose parents never attained tertiary education the effect is statistically zero in localities 20 kms or further away from where the new campuses opened.

Third row reports the effect of the policy on total enrollment. Column (1) reports an average increase of 100 students in total enrollment coming from localities where new campuses opened. Column (2) reports also a positive and significant increase of almost 80 students when considering localities 20 kms far away from the new campus, and Column (3) and Column(4) report a positive and significant increase of 57 and almost 42 new students coming from localities 30 and 50 kms away from the new campus respectively. This result suggests that the effect on total enrollment is stronger in the cities where campuses opened decreases as we increase the buffer size, but remains positive and significant even for

localities 50 kms away from the new campus.

Overall, our estimates suggest a positive and significant effect of the policy on upward intergenerational mobility at the top of the educational distribution in the localities where new campuses opened. According to the National Household Survey 80% of individuals that were 30 or less in 2019, have 12 or less years of education. That means that being a first generation university student very likely means being the first one in the family to be at the top 20% of educational distribution.[21] The difference in the effect of the policy on the two measures of mobility suggest that while having a new campus "close" to the locality of origin has an effect on enrollment for those students whose parents never enrolled in university but have tertiary education it does not have it on those whose parent at most have finished secondary education. From a policy perspective, this implies that further effort should be done in order to targeted students from localities close to the new campuses whose parents have non tertiary education.

7.2 | Results at student level

Table 3 shows the estimates of equation 3 under the same four treatment variables described before.Estimates of γ^i represent the causal effect of the policy on the conditional probability of a student being first generation conditional on having enrolled at university. In other words, estimates of γ^i show the effect of the policy on the likelihood that student who enrolled in university has parents that do not hold a university degree. We run the analysis for our two definitions of educational mobility. The first and third row show the estimates of the causal effect without controlling for individual characteristics. The second and fourth rows control for gender and age at enrollment fixed effects.

TABLE 3 Effects of the policy on the conditional probability of being first generation university student.

	Baseline	Buffer 20 kms	Buffer 30 kms	Buffer 50 kms
	(1)	(2)	(3)	(4)
First generation^{NU} -no controls	0.031***	0.032***	0.033***	0.030***
	(0.012)	(0.012)	(0.012)	(0.011)
First generation^{NU} -controls	0.028***	0.030***	0.031***	0.028***
	(0.010)	(0.010)	(0.010)	(0.009)
First generation^{NT} - controls	0.036***	0.038***	0.031***	0.044***
	(0.013)	(0.013)	(0.013)	(0.013
First generation^{NT} -no controls	0.032***	0.033***	0.034***	0.040***
	(0.013)	(0.013)	(0.013)	(0.013)
N	55,475	55,475	55,475	55,475

Notes: Standard errors clustered at locality level in parentheses. All specifications include calendar year and locality fixed effects. Controls include gender and age at enrollment fixed effects. Baseline scenario considers a locality as treated according to timeline. The final dataset is composed of students with information both in administrative records and the census in the enrollment year, aged 30 or less when entering University and with valid geographical information. Montevideo and Canelones are excluded. Sample drawn from UdelaR administrative records and Census at enrollment year. ***significant at the 1% level, **5% level, *10% level.

[21] The distribution of years of education moved to the right during the last 20 years. For individuals that were 50 or more in 2019, having 12 or more years of education means being at the top 15% of the distribution. That is why, on average, individuals enrolling in university moved up in the years of education distribution respect to their parents, but it might not be true for all students, given the 5% overlap in the years of education distribution for the different generations.

First row of Column (1) reports a 3.1% effect of the policy on the probability that an individual from the treated locations, that enrolled in university, would be a first generation university student, when considering only those whose parent never enrolled in university. These effects remains almost unchanged when considering those students whose parents never enrolled in any tertiary education program, controlling or not for individuals characteristics. The effect remains around 3% when we consider as treated those students living in localities 20, 30 and 50 kms away from the new campus. The effect is always statistically significant at a 1% level.

Results are consistent with the analyses at locality level, though more robust. Therefore, we provide evidence of a significant effect of the university geographical expansion policy in reducing spatial inequality in educational mobility in Uruguay. An increase of the conditional probability of being a first generation means a change in the share of students that enrolled in university whose parents do not hold a university degree. Even though, due to lack of data on non university students we can not estimate the unconditional probability of being a first generation, analyzing decisions at individual level allows us to control for heterogeneity in individuals characteristics, and give localities different weights depending on the number of students, something we have to abstract of when analyzing the data at locality level.

7.3 | Robustness checks and falsification exercise

The results reported in the previous section indicate that geographical campus expansion policy had a positive and significant effect on upward intergenerational mobility in those localities where new campuses opened. In this section we check the robustness of our empirical strategy by running a falsification exercise of the policy effect on intergenerational mobility in the capital, Montevideo, and on the capital plus the localities in the limiting department, Canelones. We evaluate the policy intervention as if it has started in 2008 and 2010, and then estimate equation 4. Table 4 shows the estimates for this falsification exercise.

TABLE 4 Falsification exercise: effects of the policy in Montevideo and Canelones on the share of first generation students.

	Montevideo	Montevideo and Canelones
	(1)	(2)
Policy intervention in 2008	0.003	-0.018
	(0.758)	(0.289))
Policy intervention in 2010	0.011	0.004
	(0.192)	(0.791)
N	1,895	1,895

Notes: Standard errors clustered at locality level in parentheses. All specifications include calendar year and locality fixed effects. The final dataset is composed of students with information both in administrative records and the census in the enrollment year, aged 30 or less when entering University and with valid geographical information. Only Montevideo and Canelones are considered. Sample drawn from UdelaR administrative records and Census at enrollment year. ***significant at the 1% level, **5% level, *10% level.

First row of Column(1) and Column(2) reports no significant effect of the campus expansion policy on the share of first generation students when considering it started in

2008. Results holds when considering that the policy started in 2010 as shown in the second row. Results of this falsification exercise provide robustness to our empirical strategy.

8 | CONCLUSIONS AND POLICY IMPLICATIONS

The analysis of intergenerational mobility has received a great deal of academic attention both in developed and developing countries. Yet, literature on spatial patterns of educational mobility and the role of public policies on it is still scarce. This paper sheds light on these dimensions focusing on students at the top of the distribution (i.e. university level). Using novel administrative records of students in Uruguay's public university between 2002 and 2020 we exploit a University reform that increased the number of campuses across the country , and provide causal evidence of the effect of public policies on intergenerational mobility. To that end we compute two different measures of educational mobility: the share of (first-generation) university students whose parents never enrolled in university and the share of (first-generation) university students whose parents never enrolled in any tertiary program.

The descriptive results show a significant increase in upward mobility at the top of the educational distribution. The percentage of first-generation students with non university parents increased 7 p.p in the last twenty years. Our results highlights a profound spatial inequality in educational opportunities across Uruguay. That motivated the public university to implement an important geographic expansion policy, which we evaluate in this paper.

Applying a staggered difference-in-difference model with fixed effects we estimate the impact of the university expansion on intergenerational mobility over the vertical margin. We find that the policy had a significant impact in upward educational mobility. The policy was successful both in increasing the number of students and the share of first generation in university students between 3% and 5% for localities where campuses opened and those 20 kms far away. When we consider the conditional probability of being a first-generation student , this effect remains around 3% even for students living 50 kms away from where the campus opened. To the best of our knowledge this paper is the first one to provide empirical evidence of the spatial patterns of intergenerational mobility in educational degree choices for developing countries and the effect that a policy of campus expansion has on it.

Taken together our results show that upward mobility at the top of the educational distribution increased during the last 20 years and the University expansion had helped to this. The policy impacted over and above university enrollment and diversity. Our results suggest the important role of public policies in the reduction of inequality of opportunities.

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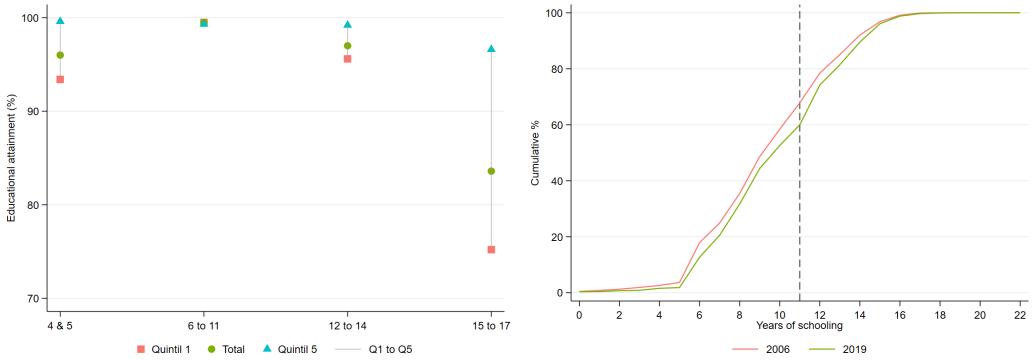
A | APPENDIX



(a) Attainment by socioeconomic level

(b) Years of schooling (ages 20-24)

FIGURE A.1 Educational context: selected indicators for Uruguay.

Notes: The figure in Panel (a) shows the percentage of people attending school by socioeconomic level for different age branches according to educational levels. Data from INEEd (2018). The figure in Panel (b) shows the cumulative distribution of years of schooling for people aged between 20 and 24. Own calculations based on NHS of the years 2006 and 2019.

TABLE A.1 Number of entry students by sex and geographical region

	Total	Capital city	Non-capital city	Male	Female
2002	7482	4881	2601	2736	4746
2003	5868	4058	1810	2286	3582
2004	7224	4519	2705	2714	4510
2005	6955	4457	2498	2674	4281
2006	6930	4289	2641	2644	4286
2007	7157	4372	2785	2752	4405
2008	6881	4375	2506	2542	4339
2009	7268	4406	2862	2673	4595
2010	7401	4587	2814	2848	4553
2011	7592	4439	3153	2830	4762
2012	7641	4570	3071	2854	4787
2013	8450	4960	3490	3279	5171
2014	9229	5513	3716	3596	5633
2015	9217	5738	3479	3732	5485
2016	12795	5994	6801	5084	7711
2017	11373	5020	6353	4407	6966
2018	13144	6054	7090	5184	7960
2019	13400	6161	7239	5340	8060
2020	12914	5832	7082	4947	7967

Notes: The table presents the distribution of the estimation sample by geographical region, gender and calendar year. The dataset is composed of students with information both in administrative records and the census in the enrollment year, aged 30 or less when entering University and with valid geographical information. Sample drawn from UdelaR administrative records and Census at enrollment year.

A.1 | Information on students' geographical origin

The dataset provides information on the center in which they accomplished their last year of secondary education. Several centers have the name of the locality included, e.g, "liceo número 1 de Colonia del Sacramento". TBC