Universidade de Brasília

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Distance Education in Brazil: Expansion, Student Profiles, and Impacts on Higher Education

Brasília, DF

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Dissertação apresentada como requisito parcial à obtenção do título de Mestre em Ciências Econômicas pela Universidade de Brasília.

Orientador: Rafael Terra de Menezes

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RESUMO

Este estudo examina a expansão da educação a distância (EaD) no Brasil, com foco no perfil dos alunos de EaD e como essa expansão tem influenciado os padrões de matrícula. Desde 2017, a EaD no Brasil experimentou grande expansão, atraindo um número crescente de alunos. Nossos resultados indicam que a EaD tem sido bem-sucedida em alcançar indivíduos mais velhos, negros, graduados de escolas públicas e com histórico acadêmico inferior em português e matemática no ensino fundamental. Esses resultados sugerem que a EaD é uma ferramenta crucial para expandir o acesso ao ensino superior, especialmente para estudantes de origens socioeconômicas desfavorecidas, ao mesmo tempo em que preserva a educação presencial para estudantes de melhor desempenho acadêmico.

Palavras-chave: Educação a Distância, Ensino Superior, Prova Brasil, Fatores Demográficos, Status Socioeconômico, Inclusão, Brasil.

ABSTRACT

This study examines the expansion of distance education (DE) in Brazil, focusing on the profile of DE students and how this expansion has influenced enrollment patterns. Since 2017, DE in Brazil has experienced significant growth, attracting an increasing number of students. Our results indicate that DE has been successful in reaching older individuals, Black individuals, public school graduates, and those with lower educational backgrounds in Portuguese and mathematics at the elementary school level. These results suggest that DE is a crucial tool for expanding access to higher education, particularly for students from disadvantaged socioeconomic backgrounds, while preserving in-person education for students with higher academic performance

Keywords: Distance Education, Higher Education, Prova Brasil, Demographic Factors, Socioeconomic Status, Inclusivity, Brazil.

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1 Introduction

Over the last nine years, Brazilian higher education institutions have significantly increased the number of available spots in distance learning courses. Between 2014 and 2022 (INEP 2022), the number of vacancies in distance learning programs grew by approximately 460%, rising from 3 million to 17 million. In contrast, vacancies in in-person programs increased by only 12%, from 5 million to 5.7 million.

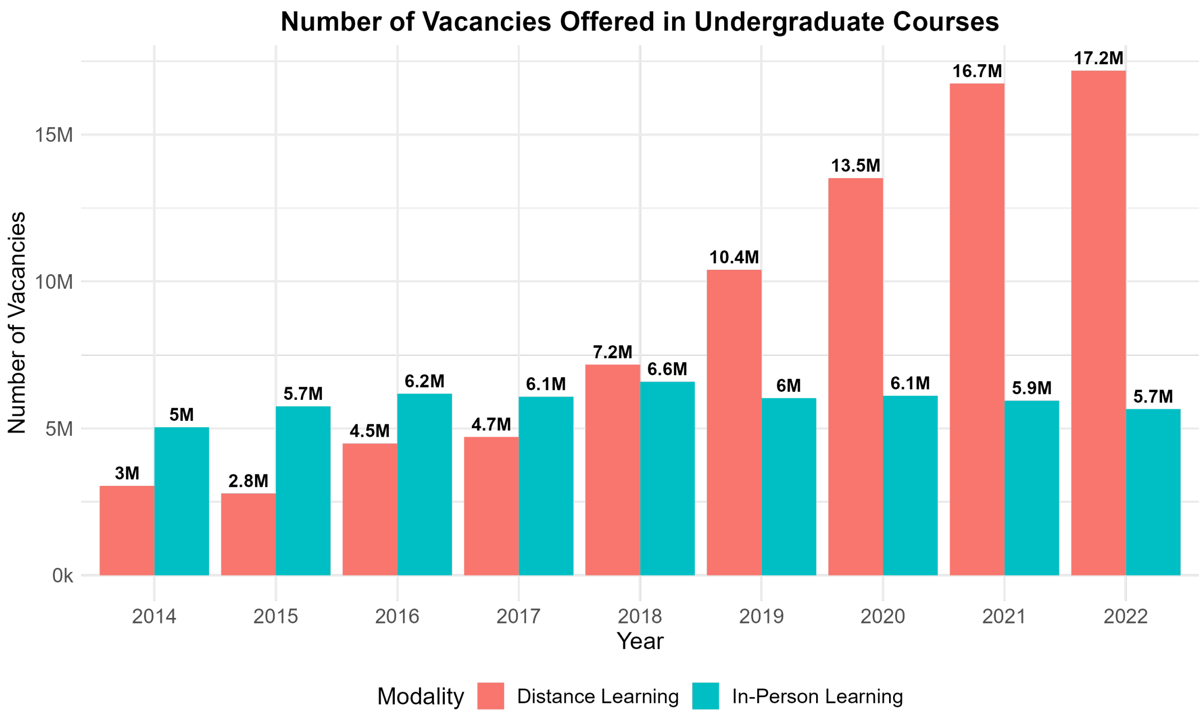

Figure 1: Number of Vacancies Offered in Undergraduate Courses, by Mode of Education. Elaborated by the author. Source: INEP 2022

Although the number of distance learning vacancies has increased significantly in recent years, the growth in first-time enrollments has been more modest. The graph above shows trends in first-time enrollments in higher education for both distance learning and in-person modalities from 2012 to 2022. First-time in-person enrollments peaked at 5.7 million in 2016 before declining to 4.3 million in 2022. In contrast, distance learning enrollments grew steadily, rising from 0.9 million in 2012 to 3.8 million in 2022.

This trend raises an important question: Has the expansion of distance learning improved access to higher education for individuals who might not have enrolled in any form of higher education otherwise? The flexibility of distance learning, such as accommodating work schedules, reducing costs, and increasing geographic accessibility, has probably encouraged

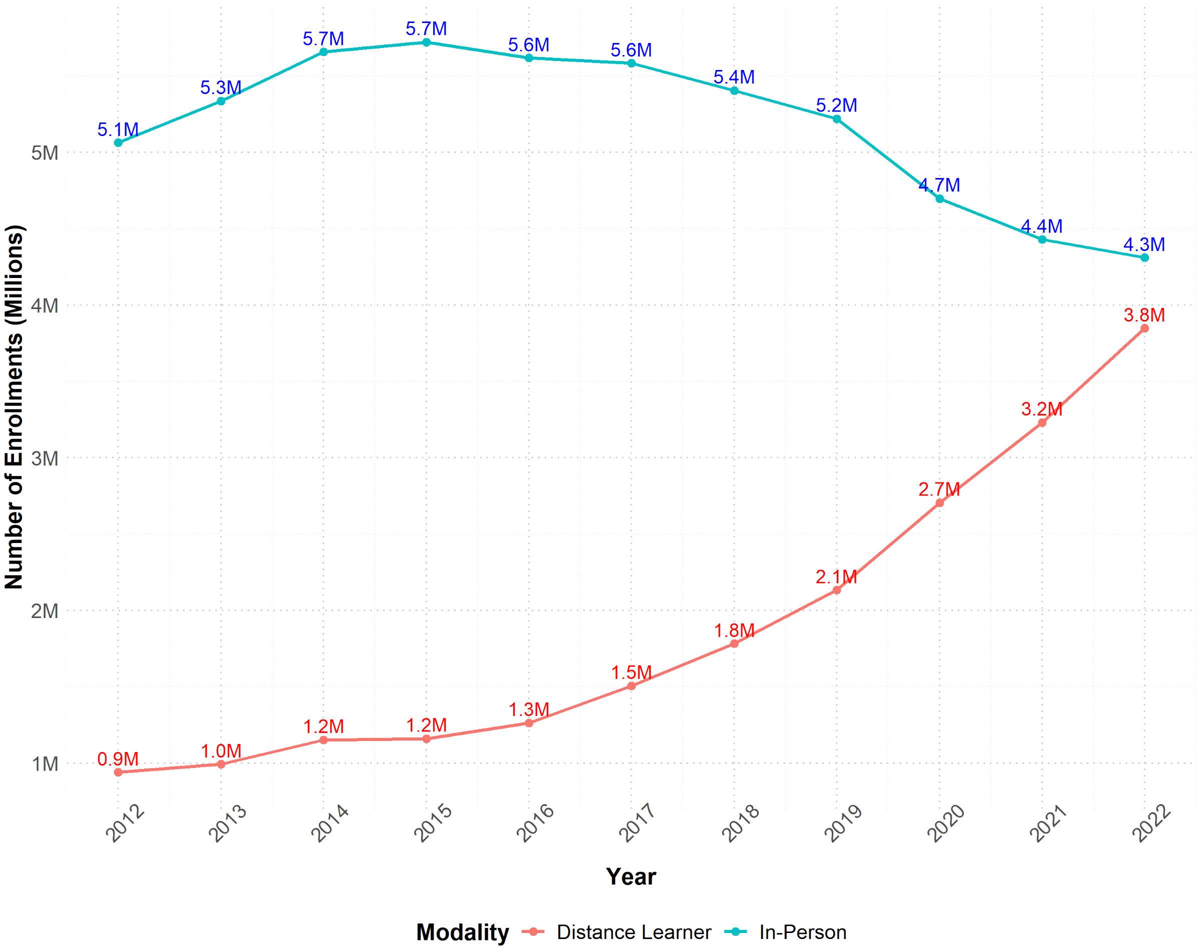

Figure 2: Number of First-Time Enrollments in Higher Education: Distance Learning vs In-Person (2012–2019). Elaborated by the author. Source: Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira (INEP) 2022

more people to pursue higher education.

To answer this question, we need to analyze whether this growth reflects a shift from in-person to distance learning or an actual increase in access for previously excluded groups. Specifically, we aim to examine the evolving profile of distance learning students over time, focusing on characteristics such as age, socioeconomic background, and academic performance. Additionally, it is essential to explore how this expansion occurred in regulatory terms and to compare the profiles of students enrolled in distance learning versus in-person modalities.

In Brazil, Art. 80 of the Education Guidelines and Bases Law (LDB), No. 9,394, of December 20, 1996 (Brazil 1996), established the legal foundation for distance learning courses. This law allowed institutions to offer courses remotely, which significantly expanded access to higher education. In 2005, the government introduced Decree No. 5,622, which regulated distance learning in detail. The decree required institutions to create equivalent in-person courses to develop distance learning programs, ensure parity in course duration, and allow credit transfers between modalities (Presidência da República Federativa do Brasil 2005).

In 2017, the government issued Decree No. 9,057, which removed the requirement for equivalent in-person courses. This change authorized institutions to focus exclusively on distance learning programs. The decree also permitted the creation of distance learning support centers (polos) with proper infrastructure, aiming to increase access to higher education. Through this regulation, the Ministry of Education (MEC) sought to achieve Goal 12 of the National Education Plan (PNE), which targeted a 50% gross enrollment rate and a 33% net enrollment rate for individuals aged 18 to 24 years (Presidência da República Federativa do Brasil 2017).

Between 2009 and 2022, distance education (DE) expanded rapidly, supported by advancements in technology. The number of DE courses increased from 848 to 9,154, and after 2018, this growth accelerated, with an average annual rate of 22%. This significant expansion reflected higher enrollments and a broader range of course offerings.

In 2024, the Ministry of Education (MEC) addressed new challenges by issuing Portaria No. 528 (Ministério da Educação 2024b). This regulation suspended the creation of new DE courses, limited the increase in vacancies, and restricted the establishment of new DE centers until March 2025. The government justified these measures by citing the rapid expansion and poor quality of some DE programs, which, according to officials, harmed students' education. The decree also required licensure and pedagogy programs, the most enrolled DE courses, to offer 50% of their coursework in person.

These regulatory changes directly impact millions of DE students. By suspending new courses and centers, the government shifted away from previous expansion policies and initiated a period of reassessment and restructuring within the sector.

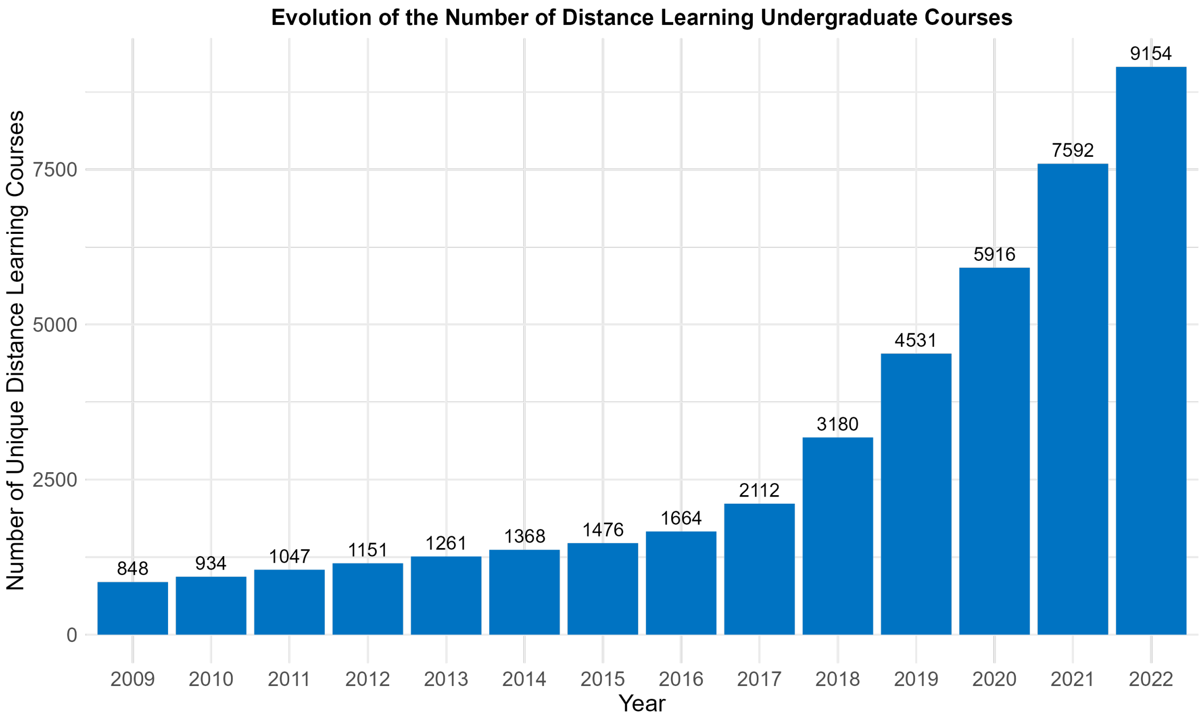

Figure 3: Number of Students by Year and Course (Distance Learning). Source: Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira (INEP) (2022), own elaboration

This work contributes to the literature by analyzing the evolving profile of distance education (DE) students in Brazil over time. Our empirical analysis highlights the significant growth in DE enrollment, particularly among students with weaker academic backgrounds in Portuguese and Mathematics during their early schooling years (up to the 9th grade). This trend underscores that distance education primarily provides an opportunity for individuals who might not have pursued higher education otherwise, expanding access to students from historically disadvantaged backgrounds.

Furthermore, our findings emphasize the role of demographic and socioeconomic factors in shaping enrollment choices. Women, older students, and individuals from Black, Indigenous, and Pardo communities, along with public school graduates, are more likely to enroll in DE. These insights demonstrate the crucial role of distance education in promoting inclusivity and providing alternative pathways to higher education for students who have historically faced barriers to traditional education.

This dissertation is structured as follows. Section 2 presents a concise literature review on distance education and includes graphs illustrating the changing profile of DE students across key dimensions such as field of study, age distribution, and high school background. Section 3 details the methodology, describing the application of logit and linear probability models to examine the determinants of DE enrollment. Section 4 presents the key empirical findings, emphasizing how DE complements in-person education rather than substituting it.

2 Literature Review and Distance Leaners' profile

2.1 Literature Review

Distance education, defined by Simonson, Smaldino, and Zvacek (2015) as "institution-based formal education in which the learning group is separated and where interactive telecommunications systems are used to connect learners, resources, and instructors", has become a cornerstone of modern higher education. This model's institutional structure and reliance on technology (e.g., online platforms, video conferencing) enable flexibility for learners to balance education with professional and personal commitments. However, as the sector expands, debates intensify about its dual role as both a democratizing force and a potential disruptor of educational quality (Deming *et al.* 2016),(Aucejo, Perry, and Zafar 2024).

From a microeconomic perspective, distance education serves as a strategy for individuals to optimize their time and resources, especially for those balancing work and family obligations. Studies conducted in the United States indicate that distance learners are typically older, predominantly female, and more likely to be employed full-time than their in-person counterparts (Latanich, Nonis, and Hudson 2001). This demographic profile reflects the appeal of the flexibility offered by distance education, enabling students to reconcile their professional and personal obligations with academic pursuits.

Psychological and motivational factors further shape the profile of distance learners. As noted by Latanich, Nonis, and Hudson (2001), individuals with an internal locus of control, who believe that they can influence their circumstances, are more inclined to choose distance education. These students tend to exhibit a higher degree of self-discipline and motivation, essential traits for success in an environment that requires independent learning and time management.

The rapid adoption of online education is undeniable. In the U.S., exclusively online enrollments surged from 15% of undergraduates in 2019 to 24% by 2022, accelerated by the COVID-19 pandemic (National Center for Education Statistics (NCES) 2022). Public institutions dominate this market (67.8% of enrollments in 2015 (Allen and Seaman 2016)), but the rise of online programs has introduced competitive pressures on traditional in-person institutions. While online education lowers tuition costs (Deming *et al.* 2016), it risks destabilizing institutions reliant on fixed operational costs, potentially reducing access to high-quality in-person options—a concern magnified in regions with limited educational infrastructure ((Deming *et al.* 2016); (Barrow, Morris, and Sartain 2024)).

The tension between democratization and quality erosion mirrors patterns observed in other sectors. For instance, community colleges expanded access to higher education but diverted some students from four-year institutions ((Rouse 1995); (Mountjoy 2022)). Similarly, online education expands access for non-traditional learners (e.g., working adults) but may divert others from higher-quality in-person programs ((Goodman, Melkers, and Pallais 2019); (Bettinger *et al.* 2017)). This dynamic parallels findings in telemedicine, where online healthcare improves efficiency but risks oversimplifying complex care ((Zeltzer *et al.* 2023); (Dahlstrand, Le Nestour, and Michaels 2024)).

This landscape contrasts with Brazil, where distance education has historically been dominated by private institutions, with limited public sector participation. While a few large private providers stand out, enrollment in Brazil remains more dispersed across many institutions, underscoring distinct regulatory and market forces that influence how distance education evolves in each country.

2.2 Distance Leaners' profile

In Brazil, the profile of distance learners mirrors some of these international trends and reflects unique socioeconomic factors. Studies by Lima, Borges, and Souza (2018) and Santos and Giraffa (2015) reveal that many Brazilian distance learners are women who balance long working hours as mothers and workers. Distance education's flexibility allows them to overcome barriers such as time constraints and the difficulty of commuting to traditional institutions. The cost-effectiveness of distance courses also plays a significant role, particularly for students from lower-income backgrounds.

While these trends are well-documented, several key questions remain unanswered. How has the demographic composition of distance education students—age, race, gender—evolved over time relative to their in-person counterparts? Are these programs reaching diverse populations, and how do enrollment trends differ between public and private institutions? The graphs below, based on census data, provide a clearer view of these trends, offering insights into the evolving profiles of students in both modalities over the past decade.

In Figures 4 and 5, we present trends in distance education (DE) across different fields. Figure 4 highlights the six courses with the highest number of distance learners: Pedagogy, Social Work, Accounting, Business Administration, Physical Education, and Human Resources. In these fields, distance enrollment (red) rose steadily from 2016 to 2022, often surpassing in-person enrollment (blue). The most dramatic increase occurred in Pedagogy, where DE enrollments nearly doubled, overtaking in-person courses by a wide margin. This sharp rise has drawn government attention, leading to new regulations requiring at least 50% of coursework for licentiate degree programs to be conducted in person starting in 2024 (Ministério da Educação 2024a).

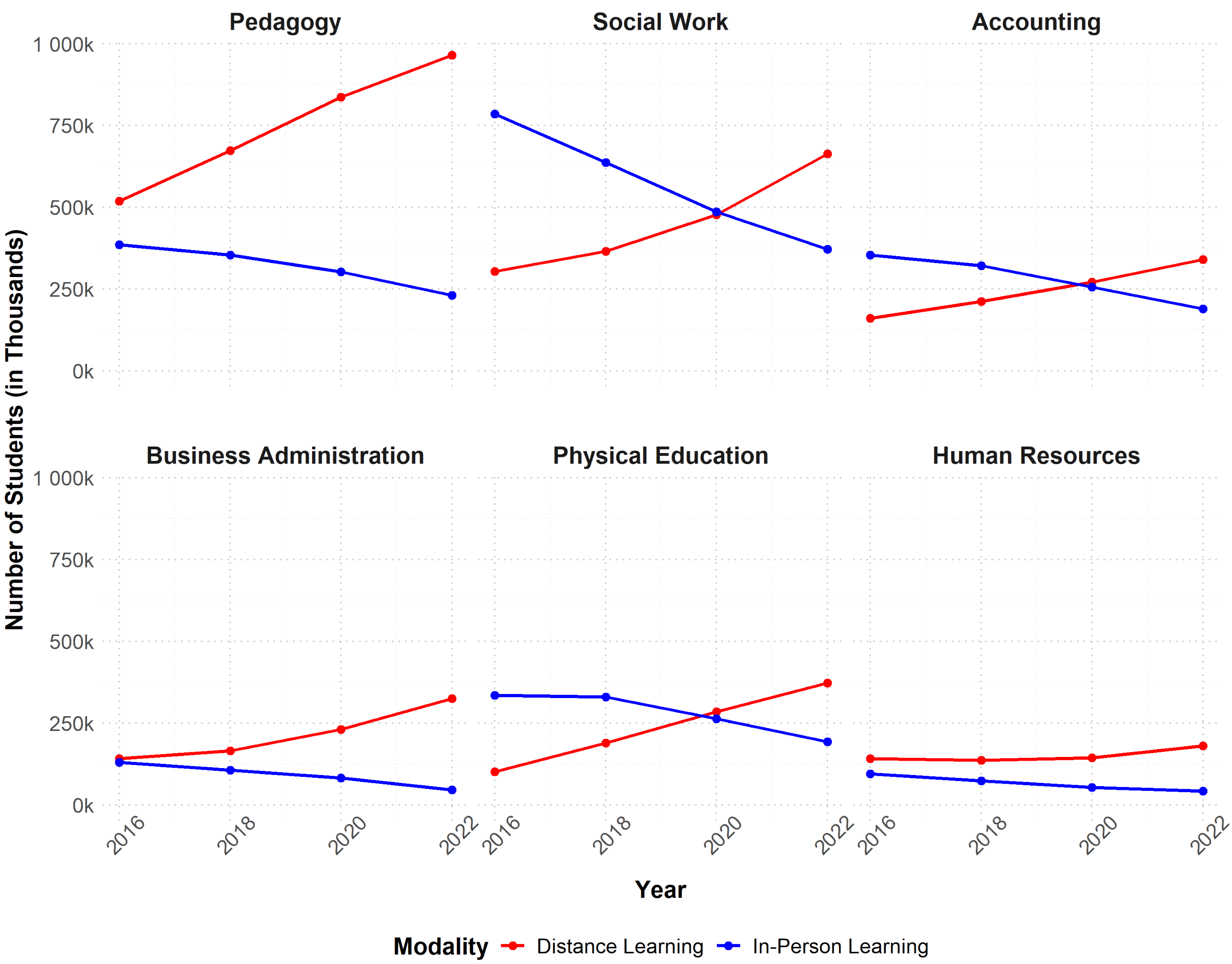

Figure 4: Total Enrollment by Course and Learning Modality (2016–2022).

Figure 5 shows trends in STEM fields—Mathematics, Biological Sciences, Civil Engineering, Chemistry, and Physics—to illustrate how distance learning is developing in the sciences. While distance education is gaining traction, the growth is more moderate compared to non-STEM fields. Civil Engineering shows the most significant shift, with in-person enrollments dropping sharply and distance enrollments rising. In Mathematics and Biological Sciences, in-person enrollment declines gradually, while online participation grows, leading to convergence by 2022. Chemistry and Physics maintain relatively low enrollment overall, though distance learning is slowly increasing. These trends suggest that even traditionally hands-on STEM fields are seeing a gradual shift toward online education, though less pronounced than in non-STEM areas.

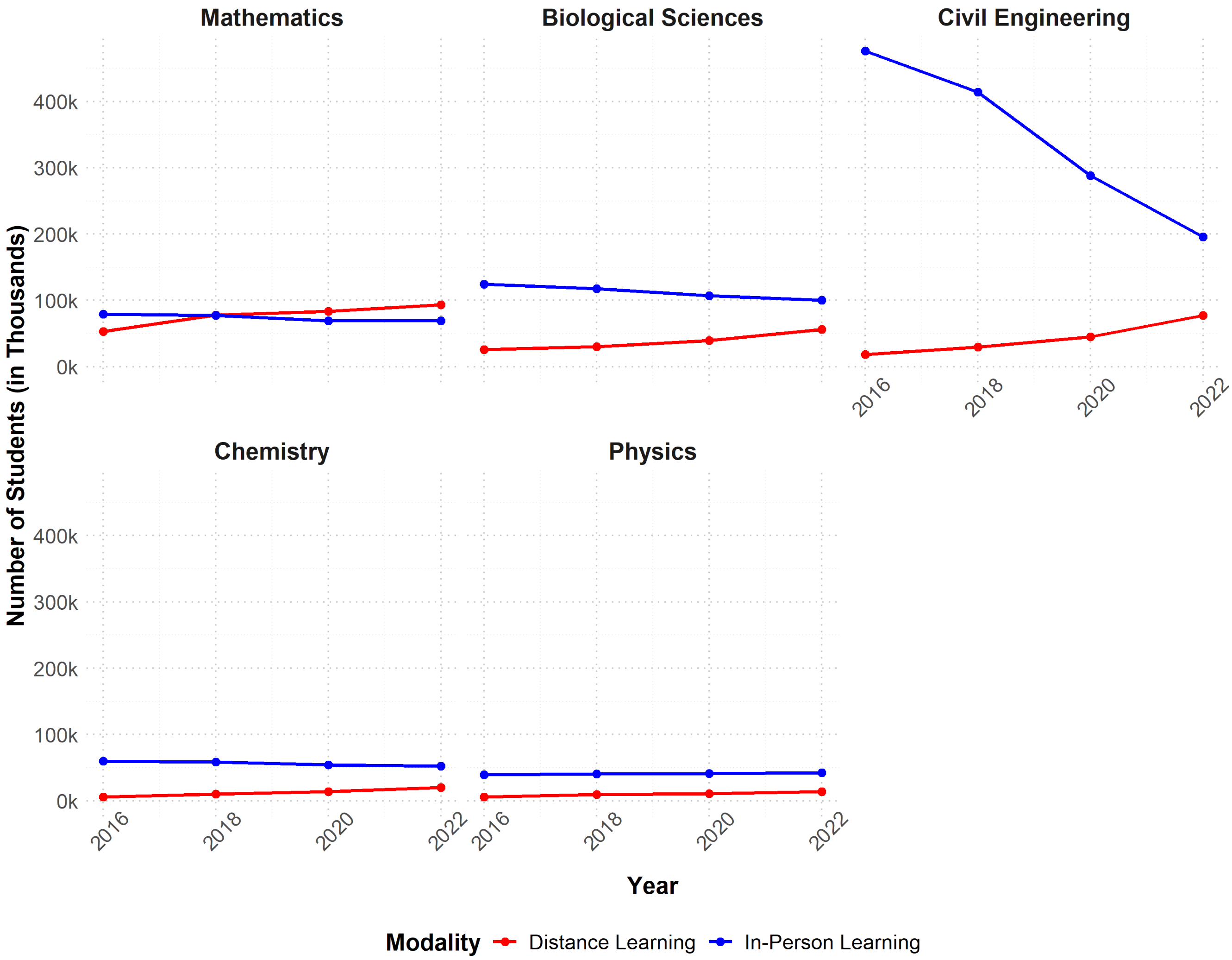

Figure 5: STEM Enrollment by Learning Modality (2016–2022).

Figures 6 and 7 below show the age distribution of new entrants in higher education for 2016 and 2022, comparing in-person and distance learning. As expected, distance learners are generally older than in-person students, whose ages cluster around 18 to 22. However, by 2022, the age distribution for distance learners shifted slightly younger compared to 2016, suggesting that younger students are increasingly choosing distance education. This reflects a growing acceptance of online learning among traditional college-age students, though older learners still represent a significant share.

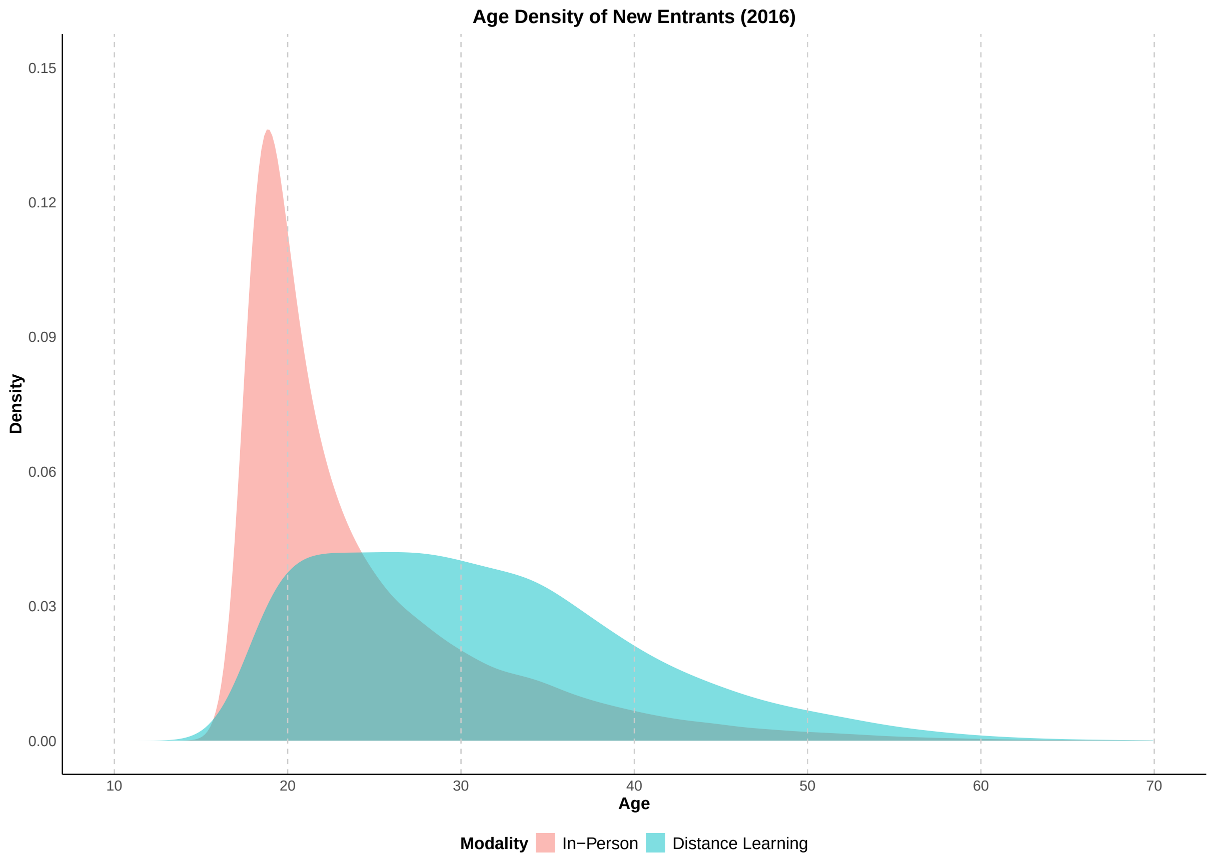

Figure 6: Age Distribution by Learning Modality (2016).

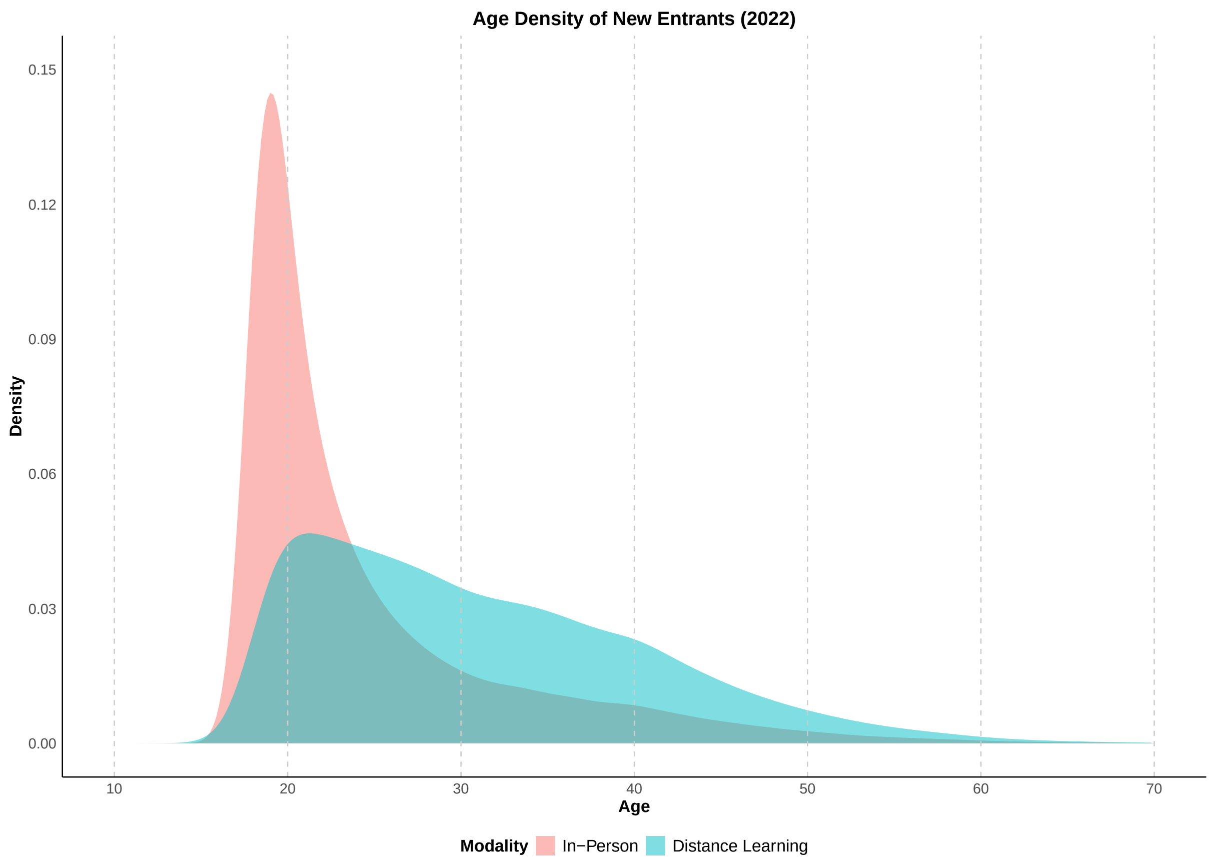

Figure 7: Age Distribution by Learning Modality (2022).

Figure 8 above illustrates the race and gender distribution in in-person and distance learning from 2012 to 2018. By 2018, distance education had become more diverse, with the share of Black students increasing to 29% and White men dropping to 31.5%. This shift suggests that distance learning became increasingly accessible to racially diverse groups over time.

It is also important to note that from 2018 to 2022, the proportion of women in distance education grew relative to in-person programs. A likely explanation is the expansion of distance courses in teaching credentials and pedagogy, which have historically enrolled more women. Consequently, both racial diversity and the representation of women appear to have grown alongside the broader adoption of distance learning in recent years.

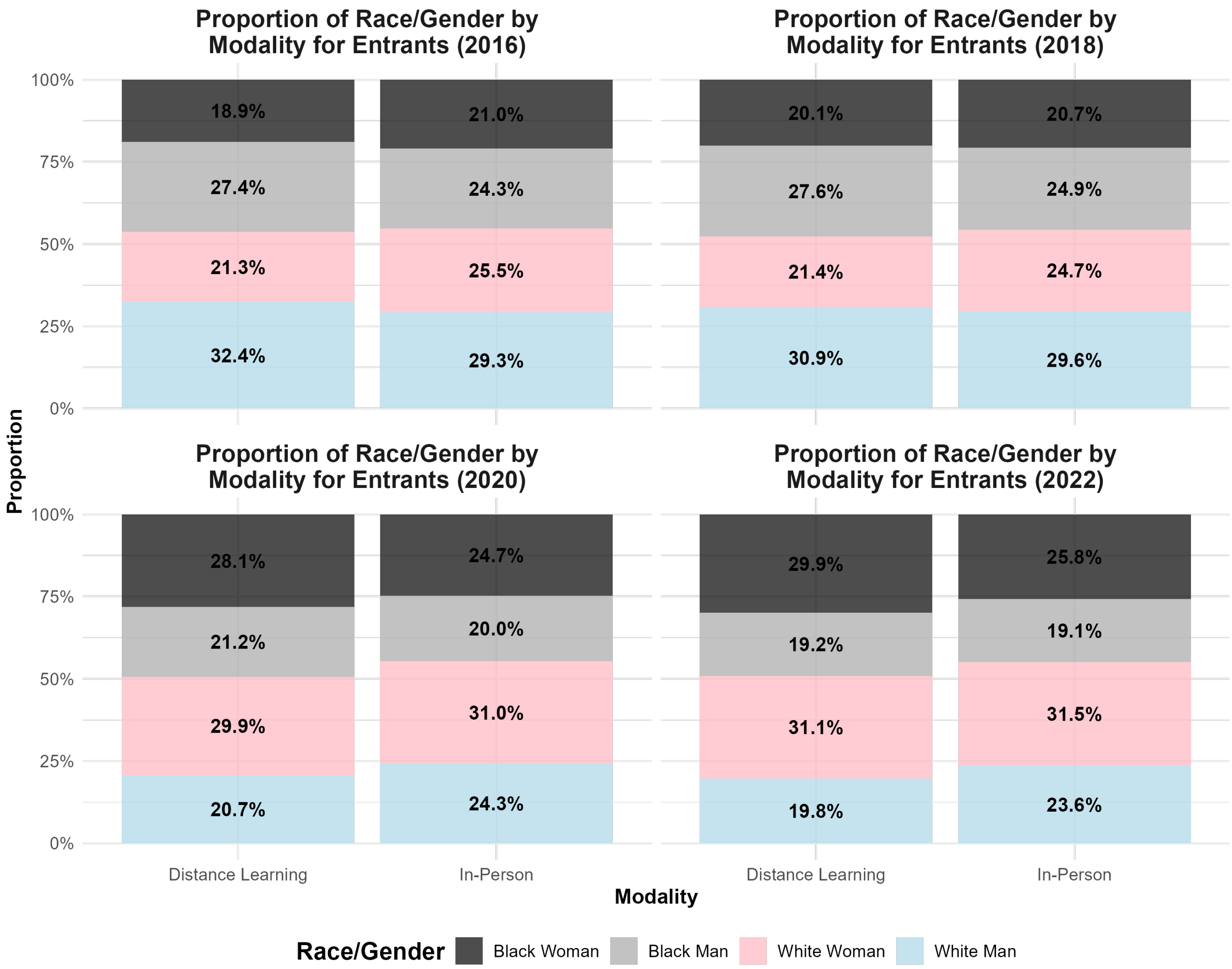

Figure 8: Racial and Gender Composition of New Students by Learning Modality (2016–2022).

Figure 9 shows the proportion of college entrants from public and private high schools in in-person and distance learning programs from 2016 to 2022. Public school graduates consistently make up the majority of distance learners (83.5% in 2016, dropping slightly to 79.7% in 2022). In contrast, private school graduates increased modestly in distance education, from 16.5% to 20.3% over the same period, suggesting a broader appeal of online programs across different backgrounds.

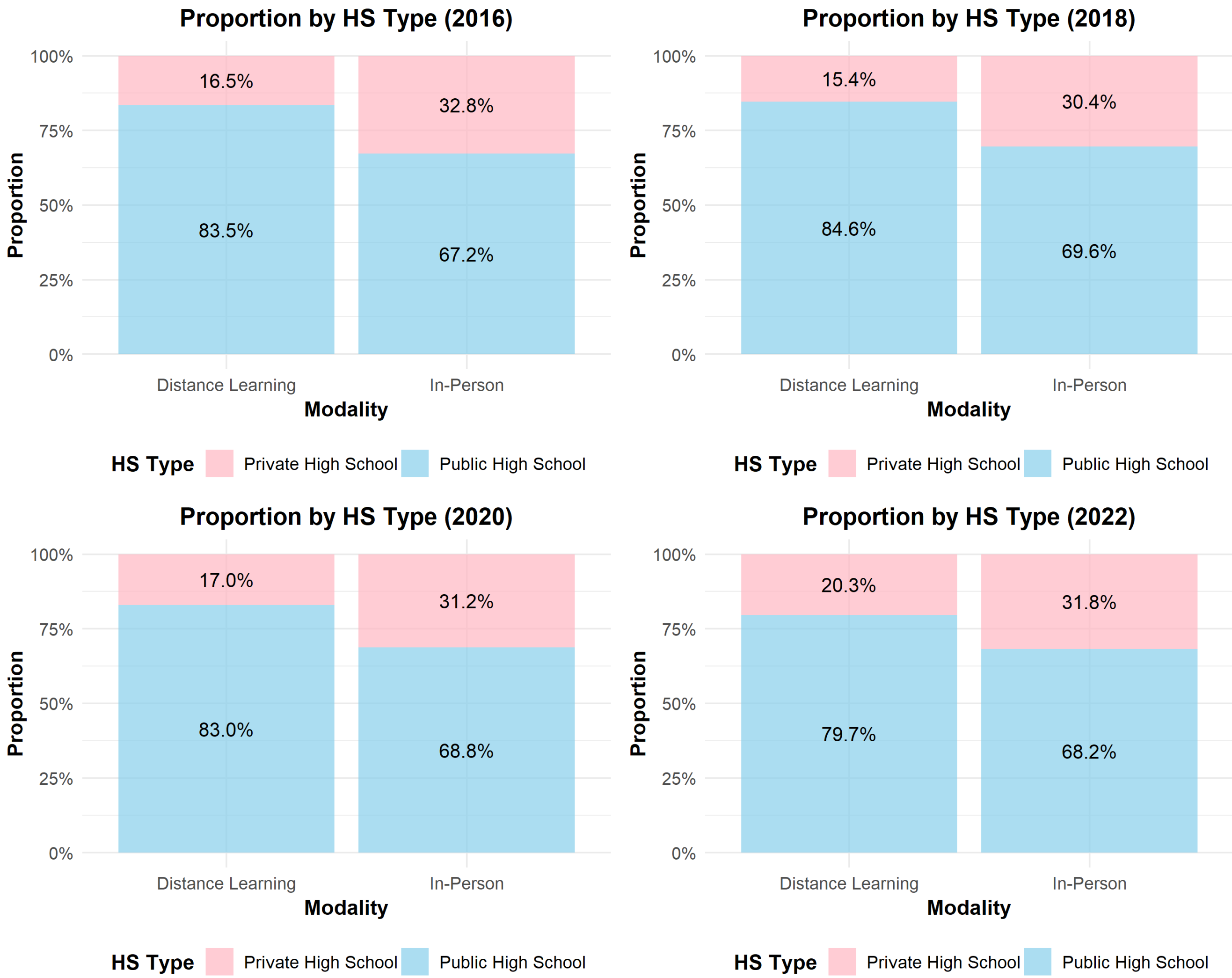

Figure 9: High School Background of College Entrants (2016, 2018, 2020, 2022).
Note: This figure shows the proportion of students entering college through in-person or distance learning programs, based on whether they graduated from public or private high schools.

Figure 10 shows university entrants by institution type and learning modality from 2016 to 2022. Over 97% of distance learning students enrolled in private universities throughout the period, while public universities saw a modest rise in in-person enrollment from 22.9% in 2016 to 27.5% in 2022. This reflects the dominance of private institutions in distance education and a stronger public presence in in-person learning.

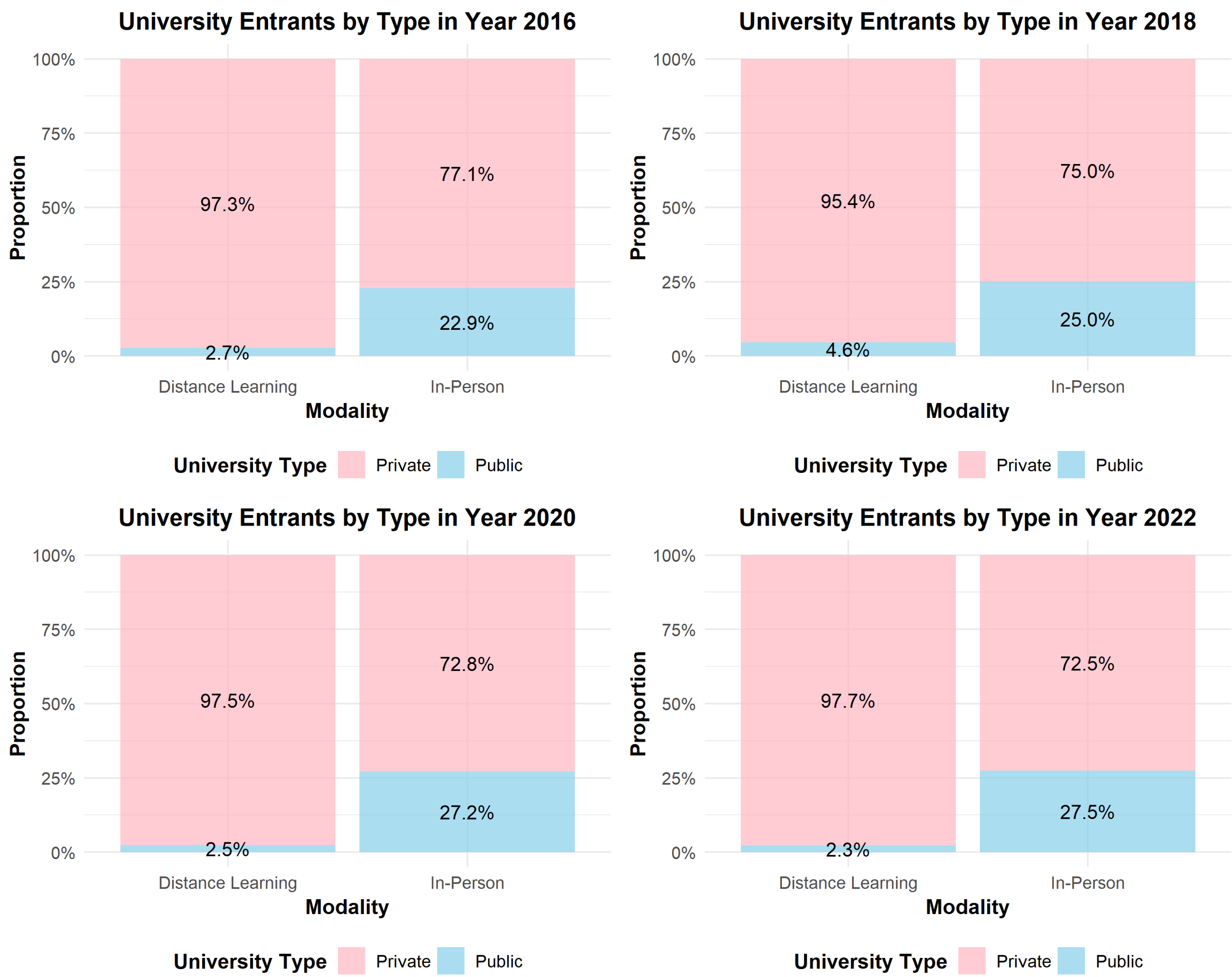

Figure 10: Enrollment by University Type and Learning Modality (2016, 2018, 2020, 2022).

Figure 11 shows ENEM usage among distance learning and in-person university entrants from 2016 to 2022. Less than 10% of distance learners used the ENEM by 2022, while in-person entrants consistently showed higher usage, around 30%. This highlights that distance education relies less on standardized exams, unlike in-person programs.

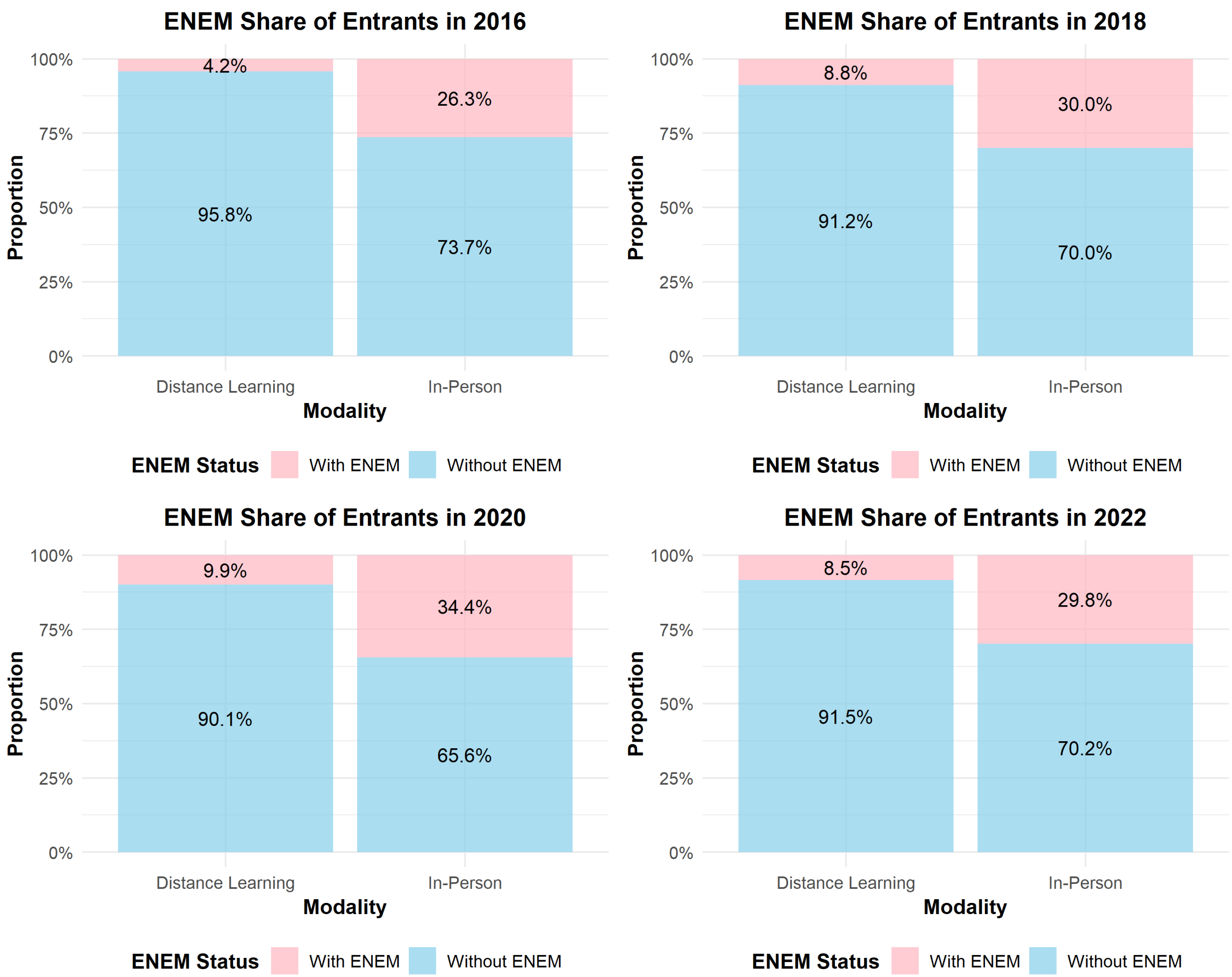

Figure 11: Pathways to Higher Education: ENEM vs. Non-ENEM Admissions (2016, 2018, 2020, 2022).

Figure 12 shows quota and non-quota entrants in distance and in-person programs from 2016 to 2022. Distance learning had less than 1% quota students, while in-person programs maintained around 8-9%. This indicates affirmative action policies are largely absent in distance education.

Figure 12: Quota vs. Non-Quota Enrollment by Learning Modality (2016, 2018, 2020, 2022).

Note: All figures in this chapter are based on data from the Higher Education Census (INEP, 2016, 2018, 2020, 2022). Own elaboration.

3 Data

The School Census is an annual dataset that tracks students from kindergarten to high school in Brazil. Schools report information on each student, including enrollment status, gender, race, grade level, and school affiliation. The Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira (INEP), a research body under the Ministry of Education, compiles and publishes these records.

ENEM consists of four objective exams—Natural Sciences, Humanities, Languages, and Mathematics—based on Item Response Theory (IRT), plus a writing test. Originally created in 1998 to assess high school education quality, ENEM has since become the primary gateway to public universities. It also serves as the basis for scholarships (ProUni) and student loans (FIES). Other public programs, like study-abroad scholarships, also require ENEM scores. Additionally, students older than typical high school age can earn their diplomas by achieving a minimum score on ENEM.

The Higher Education Census, available since 2007, includes data on all students enrolled in higher education institutions. It shows their enrollment status, type of entrance exam, sources of funding, chosen major, and institutional details. It also identifies whether students participate in distance-learning or in-person programs, providing a detailed view of their higher education experience.

The Brazilian Ministry of Labor compiles the Annual Social Information Report (RAIS), which records all formal labor contracts in the country. Each entry represents an employer-employee relationship, detailing contract status at year-end, duration, wages, and hours worked. The confidential version of RAIS covers 2009–2021. However, RAIS excludes informal workers who lack legal employment contracts, making it an incomplete representation of the entire labor market.[1] To estimate the informal sector, researchers must rely on secondary sources, such as demographic surveys. Since administrative data does not capture informal employment, this segment remains outside the main analysis.

The School Census is not directly linked to post-secondary education and labor market datasets, such as the Higher Education Census and RAIS. However, it assigns a unique student ID[2] that enables INEP to merge records across datasets. Although the Higher

[1] A single data source, such as the Brazilian demographic census or the PNAD surveys, allows for estimating the relative size of the informal sector, wage distribution, employment duration, and other key aspects of this labor market segment. For more details, see Dix-Carneiro and Kovak 2016.

[2] Cadastro de Pessoa Física (CPF), anonymized for privacy

Education Census and RAIS primarily use the social security number as their identifier, the CPF-based linkage ensures a reliable connection between school, college, and employment records.

Students who take the National Exam of Upper Secondary Education (ENEM) provide their social security number during registration, enabling INEP to link the School Census ID to the social security number for most participants. INEP can also obtain CPF data from schools or higher education institutions, which allows tracking some students even if they do not take the ENEM[3]

Since 2005, Brazil administers Prova Brasil (Brazil's exam) every odd-numbered year to students in the 5th and 9th grades of public primary schools. Identified individual data became available starting in 2011. Despite its broad coverage, Prova Brasil has key limitations: it excludes multi-grade classrooms, adult education programs, and indigenous schools, leaving educational outcomes of vulnerable groups largely unknown. Additionally, participation is voluntary for private schools, and SAEB only includes classes with more than 20 students, further limiting the representativeness of smaller or more remote schools. Still, the exam offers valuable insights into student performance, enabling heterogeneity analyses based on prior proficiency.

Our dataset is based on annual microdata from the Brazilian School Census (2007–2021). Given computational constraints, processing the full census across multiple years is impractical. Instead, we draw a stratified random sample of 50,000 9th-grade students per year, ensuring representativeness by state, gender, school type, and race. Each cohort corresponds to a specific year when students were in the 9th grade within the respective sample. For instance, students who were in the 9th grade in 2007 in our sample belong to cohort 1, those in 2008 form cohort 2, and so on up to cohort 7, which corresponds to students who were in the 9th grade in 2013 in our sample

Although structured as a single longitudinal panel, our dataset allows for cohort-specific analyses while maintaining a unified framework. We track each cohort through 2021, linking School Census data with records from the High School Census, ENEM, Higher Education Census, and RAIS to analyze educational and labor market trajectories for all students in all cohorts.

[3] Approximately 74% of all students in the INEP database have a masked student ID (CPF), enabling us to link data from the education census to RAIS and the higher education census. Attrition due to missing CPF occurs largely at random because some students do not take the ENEM, and some schools and higher education institutions do not provide CPF data to INEP.

This cohortal structure is critical because each cohort faced different institutional and national contexts. For example, the expansion of distance learning (DE) from 2017 onward significantly increased access to higher education, meaning that two close cohorts, such as cohort 5 (2011) and cohort 7 (2013), had different exposure to distance learning opportunities.

In addition, we obtained Prova Brasil data for approximately 70% of the students in each of the 2011 and 2013 samples, corresponding to cohorts 5 and 7, respectively. This allows us to compare students with similar initial proficiency levels, enhancing the validity of our analysis by accounting for differences in prior academic achievement.

The 2014 Brazilian School Census data show dropout rates across different grades. That year, 12.7% of first-year and 12.1% of second-year high school students left school. Ninth-grade students had the third-highest dropout rate at 7.7%, followed by third-year high school students at 6.7%, with an overall high school average of 11%. In contrast, earlier grades had much lower dropout rates, such as 2.8% in the 7th grade.

Focusing on 9th-grade students captures a key transition point when dropout rates start rising. This approach ensures our dataset reflects the broader student population while reducing selection bias, as younger grades have lower dropout rates. Additionally, the dropout rates in our sample align with census data, confirming the reliability of our dataset for studying educational paths.

Table 1 summarizes key educational and labor market choices for cohort 5 (2011). Among students, 25.4% enroll in in-person college programs, 4.6% in distance education, 11.3% study exclusively, and 27.7% combine college with formal work. Overall, 42.2% participate in formal employment, with 31.2% working without pursuing higher education.

Regarding institutions, 8% attend public colleges, while 42% enroll in private ones, often supported by ProUni and FIES. Admissions split across vestibular (37%), ENEM (20.2%), and quotas (5.1%).

Table 2 presents cohort 7 (2013). Here, 14% enroll in in-person college, 11.5% in distance education, 8.8% study exclusively, and 13% combine studies with work. In total, 38.8% engage in formal labor, with 28% working only. Public college enrollment drops to 5.2%, while private institutions account for 22.3%. Admissions rely on vestibular (27.3%), ENEM (16.6%), and quotas (3.4%).

The differences between cohorts reflect their exposure to educational and labor market opportunities. cohort 5, with two extra years of observation, shows higher participation in college and work. cohort 7 coincides with an expansion of distance education, increasing its adoption.

The descriptive statistics for cohort 5 (2011) and cohort 7 (2013) are presented here. These two cohorts are the main focus of this analysis because they are the only cohorts for which we have Prova Brasil data for 9th-grade students. This allows us to compare students with similar initial proficiency levels in subjects like Portuguese and Mathematics, offering a more accurate analysis of their educational and labor market outcomes.

The other cohorts (1 to 4 and 6) lack Prova Brasil data for 9th-grade students, which limits our ability to perform the same level of comparison for those cohorts. Therefore, we focus on cohorts 5 and 7 for the descriptive statistics, as these are the cohorts with available data for the baseline test scores.

Table 1: Descriptive Statistics for cohort 5

Variable	Nobs	Mean	SD
Sample			
Women	50000	0.485	0.5
Progression through high school			
Advanced to 1st year on time	50000	0.76	0.426
Advanced to 3rd year on time	50000	0.52	0.512
Prova Brasil baseline test scores			
Language	31925	243.310	42.346
Math	31877	250.734	43.012
ENEM's test scores			
ENEM's test score selection	50000	0.30	0.377
Nature Sciences	15039	472.028	68.304
Human Sciences	15039	524.726	78.202
Language	15039	506.962	66.017
Math	15039	474.533	98.000
Human capital decisions			
College (in-person)	39322	0.254	0.361
College (distance education)	39322	0.046	0.209
Labor	39322	0.422	0.452
Only college	39322	0.113	0.325
Only labor	39322	0.312	0.493
College and labor	39322	0.277	0.458
College administration			
Public	39322	0.083	0.270
Private	39322	0.424	0.493
College admission			
Vestibular	39322	0.373	0.483
ENEM	39322	0.202	0.401
Quotas	39322	0.051	0.221
Financing	39322	0.253	0.433

NOTE — Descriptive statistics. ENEM's test scores refer to the expected senior year of high school (2014), while Prova Brasil test scores are from 2011. The college indicator equals 1 if an individual is enrolled in any college-major during the analyzed period. Labor equals 1 if an individual has a formal work agreement in the same period. Only college equals 1 if an individual is enrolled in a college-major but does not have a formal work agreement, while Only labor equals 1 if the individual is only working. College and labor equals 1 if an individual is both enrolled in a college-major and has a formal work agreement. College administration and college admission proportions can exceed the overall proportion of students in college because a student can be enrolled in more than one college-major during the analyzed period. Financing refers to programs such as ProUni and FIES, which are mostly used in private institutions, reflecting the higher prevalence of private colleges in the dataset. Approximately 76% of students in cohort 5 were identified using masked CPF data.

Table 2: Descriptive Statistics for cohort 7

Variable	Nobs	Mean	SD
Sample			
Women	50000	0.492	0.48
Progression through high school			
Advanced to 1st year on time	50000	0.72	0.476
Advanced to 3rd year on time	50000	0.58	0.488
Prova Brasil baseline test scores			
Language	31844	242.724	43.354
Math	31212	249.254	44.467
ENEM's test scores			
ENEM's test score selection	50000	0.28	0.420
Nature Sciences	9395	471.500	67.800
Human Sciences	9395	523.832	77.500
Language	9280	507.242	65.800
Math	9280	475.356	97.500
Human capital decisions			
College (in-person)	27532	0.142	0.347
College (distance education)	27532	0.115	0.238
Labor	27532	0.388	0.440
Only college	27532	0.088	0.300
Only labor	27532	0.281	0.485
College and labor	27532	0.139	0.450
College administration			
Public	27532	0.052	0.233
Private	27532	0.223	0.462
College admission			
Vestibular	27532	0.273	0.423
ENEM	27532	0.166	0.388
Quotas	27532	0.034	0.180
Financing	27532	0.182	0.393

NOTE — Descriptive statistics. ENEM's test scores refer to the expected senior year of high school (2016), while Prova Brasil test scores are from 2013. The college indicator equals 1 if an individual is enrolled in any college-major during the analyzed period. Labor equals 1 if an individual has a formal work agreement in the same period. Only college equals 1 if an individual is enrolled in a college-major but does not have a formal work agreement, while Only labor equals 1 if the individual is only working. College and labor equals 1 if an individual is both enrolled in a college-major and has a formal work agreement. College administration and college admission proportions can exceed the overall proportion of students in college because a student can be enrolled in more than one college-major during the analyzed period. Financing refers to programs such as ProUni and FIES, which are mostly used in private institutions, reflecting the higher prevalence of private colleges in the dataset. Approximately 55% of students in cohort 7 were identified using masked CPF data.

4 Empirical Strategy

4.1 Logit Model

In this section, following (Carvalho, Cajueiro, and Camargo 2015), we analyze the profile of students enrolled in Distance Education (DE) compared to those in traditional in-person education between 2016 and 2021. Our goal is to identify what distinguishes DE students from in-person students and how these differences change over time.

To do this, we use a logistic regression model, which is ideal for cases where the dependent variable is binary. In our case, the dependent variable indicates whether a student is enrolled in DE (1) or in-person education (0) The logit model can be expressed as:

$$p_i = P[y_i = 1|x_i] = F(x_i'\beta) \tag{1}$$

Where y_i is the binary outcome variable, taking the value of 1 if the student is enrolled in DE, and 0 if the student is enrolled in in-person education. x_i represents the vector of explanatory variables for the student i, and β is the vector of coefficients to be estimated. The function $F(.)$ is the cumulative distribution function (CDF), typically the logistic function, which ensures that the predicted probabilities are within the [0, 1] range.

The general model can be expressed as:

$$\text{DE\_enrollment} = X\beta + u \tag{2}$$

Where DE_enrollment is the binary outcome variable indicating enrollment in Distance Education (DE), X is the matrix of explanatory variables, β is the vector of coefficients to be estimated, and u is the error term.

The likelihood function for the logistic model is given by the following expression:

$$L = \prod_{i=1}^{n} F(x_i'\beta)^{y_i} \left[1 - F(x_i'\beta)\right]^{1-y_i} \tag{3}$$

Where L is the likelihood of observing the data, n is the number of observations, and y_i is the observed outcome for the i-th observation. The logistic function $F(x_i'\beta)$ is typically defined as:

$$P(y_i = 1) = \frac{1}{1 + \exp(-x_i'\beta)} \tag{4}$$

where exp represents the exponential function, and β is the vector of coefficients.

In the analysis, we estimate the coefficients β using maximum likelihood estimation (MLE) for the years 2016 to 2021. The estimated coefficients reflect the log-odds of enrolling in DE. To make interpretation easier, we exponentiate these coefficients to obtain odds ratios (ORs). The OR tells us how much more (or less) likely a student with a given characteristic is to enroll in DE instead of in-person education. If OR $>$ 1, the characteristic increases the likelihood of choosing DE. If OR $<$ 1, it reduces the likelihood compared to the reference group.

In our empirical analysis, we track the cohorts from 2007 to 2013 over time and identify all students who were enrolled in higher education between 2016 and 2021, regardless of whether they were new entrants or continuing students. We combine all the cohorts (1 to 7) to analyze the profile of students who were enrolled in higher education during this period. The logit model is applied to the merged data from all cohorts, allowing us to examine the likelihood of enrollment in Distance Education (DE) compared to in-person education.

Our dependent variable is binary: 1 if the student is enrolled in DE and 0 if they are in in-person education. The explanatory variables include demographic factors (gender, age, and race), socioeconomic background (whether they attended public school, received financial aid, or participated in affirmative action programs), and labor market engagement (whether they work while studying). These covariates allow us to more specifically examine the profile of DE students using a logistic regression model.

The table below describes the covariates used in our model and their definitions.

Table 3: Description of the covariates used in the logit model

Covariate	Description
race_black	A binary variable indicating the student's racial background (1 for students identifying as Black, Indigenous, or Pardo, and 0 for students identifying as White or Yellow).
female	A binary variable indicating the student's gender (1 if the student is female, 0 otherwise).
age	The student's age.
age2	The square of the student's age, used to capture non-linear age effects.
work_and_study	A binary variable indicating whether the student works while studying (1 if yes, 0 if no).
public_high_school	A binary variable indicating whether the student attended a public high school (1 if yes, 0 otherwise).
financing	A binary variable indicating if the student has access to financial aid (1 if yes, 0 otherwise).
affirmative_action	A binary variable indicating whether the student is part of a special admission program (1 if yes, 0 otherwise).

4.2 Linear Probability Model

This section examines how the expansion of distance education (DE) has influenced higher education enrollment among students with different academic backgrounds. Using Linear Probability Models (LPMs), we estimate the likelihood of enrolling in DE versus in-person programs for two specific cohorts: cohort 5 (students who took the 9th-grade SAEB/Prova Brasil exam in 2011, expected to graduate from high school in 2014) and cohort 7 (students who took the exam in 2013, expected to graduate from high school in 2016). These two cohorts faced different levels of DE availability, allowing us to assess how broader access to DE affected enrollment decisions

Unlike the logit model, which includes all cohorts (1 through 7) to analyze the overall profile of students enrolled in higher education, the LPM focuses specifically on cohorts 5 and 7, as these are the only cohorts with available Prova Brasil data. This allows us to perform a more detailed analysis of enrollment trends among students with different academic backgrounds, measured by their Prova Brasil performance.

To analyze the role of academic performance, we rank students based on their SAEB/Prova Brasil scores and assign them a percentile within their respective cohorts. We then divide them into four quartiles (0–25, 25–50, 50–75, and 75–100) and estimate separate models for each group. This segmentation allows us to compare students with similar academic backgrounds, which avoids diluting differences in an overall average. It also helps determine whether the DE expansion primarily benefited lower-performing students or if trends are consistent across performance levels.

Following (Greene 2003), we use a linear probability model to estimate the likelihood of enrollment. Our analysis considers two binary dependent variables:

1. **Enrollment in DE vs. all other options**: Takes the value 1 if the student enrolls in a DE program and 0 otherwise. The reference group includes students who either enroll in in-person education or do not pursue higher education.

2. **Enrollment in in-person education vs. all other options**: Takes the value 1 if the student enrolls in an in-person program and 0 otherwise. The reference group consists of students who either enroll in DE or do not enter higher education.

The regression equation is given by:

$$y_{it} = \alpha + \beta_1 \,\text{PB\_Percentile\_Rank}_i + \beta_2 \, X_i + \varepsilon_{it}, \tag{5}$$

where y_{it} represents enrollment in either DE or in-person education, $\text{PB\_Percentile\_Rank}_i$ denotes the student's percentile rank, and X_i includes controls for race, gender, age, public high school attendance, and work-study status.

We track students for five years after their expected high school graduation—2015–2019 for cohort 5 and 2017–2021 for cohort 7. This timeframe allows us to observe how enrollment patterns evolve, including both the immediate post-high school period and subsequent years. cohort 7, with greater exposure to DE opportunities, allows us to assess whether its expansion influenced enrollment decisions differently across academic backgrounds, compared to cohort 5.

Rather than focusing on individual regression coefficients, we analyze the average enrollment probability for each control group — DE vs. all and in-person vs. all—over time and across different performance percentiles. This approach helps determine whether DE is a substitute for in-person education or a complementary option. If lower-performing students (0–25 percentile) show a larger increase in DE enrollment, while higher-performing students maintain or increase in-person enrollment, it suggests that DE serves as a substitute for those facing higher barriers. Conversely, if DE enrollment grows across all quartiles alongside in-person enrollment, it indicates that DE expands access rather than replacing existing pathways.

For brevity, the full regression results, including 20 tables, are provided in the appendix.

5 Results

5.1 Profile of Distance Higher Education Students

This section presents the results from the logistic regression model, where we estimate the odds ratios for enrolling in distance education (EAD) instead of in-person education from 2016 to 2021. Unlike the linear probability model (LPM), which focuses specifically on cohorts 5 and 7, this model uses data from all cohorts (1 through 7), enabling us to analyze the overall profile of students enrolled in higher education during this period.

Table 4 above presents the odds ratios from the logistic regression estimating the probability of enrolling in distance education (EAD) instead of in-person education from 2016 to 2021. The results show that women are consistently more likely to enroll in EAD than men, with their likelihood being at least 20–50% higher, depending on the year. This trend suggests that EAD's flexibility particularly benefits women, especially those balancing work and household responsibilities.

Race also influences enrollment choices. Black, Indigenous, and Pardo students are 10–40% more likely to choose EAD than White and Yellow students, with this effect being strongest in earlier years. Similarly, public school graduates are more than twice as likely to enroll in EAD compared to private school students, reinforcing the role of distance education in expanding access to historically disadvantaged groups in Brazil.

Age plays a key role as well. Older students are more likely to enroll in EAD, but this effect weakens at higher ages. The squared age term, which is statistically significant in 2020 and 2021, suggests that while EAD attracts older students, very late transitions into higher education become less common.

Employment trends also shift over time. Initially, students who worked while studying were less likely to choose EAD. However, from 2020 onward, this trend reversed, making working students more likely to enroll in distance education. This change likely reflects the increasing compatibility of EAD with employment.

Financial aid patterns evolve over the years. Until 2019, students with financial aid were less likely to be in EAD. However, from 2020 onward, this relationship reversed, suggesting that financial support became more accessible to distance learners. This shift likely results from policy changes expanding funding for EAD students.

Affirmative action policies appear to favor in-person education. Students benefiting from these policies were much less likely to enroll in EAD, particularly in 2016 and 2021. This suggests that quotas primarily support in-person programs, potentially limiting their reach in distance education.

Overall, EAD enrollment has grown significantly, with the proportion of students choosing distance learning increasing from 9.4% in 2016 to 35.2% in 2021. Beyond individual characteristics, structural factors such as educational supply, financial aid, and labor market conditions have played a crucial role in this expansion.

Table 4: Logit Model Odds Ratios by Year

Covariate	**2016-2018**		**2019-2021**			
	2016	2017	2018	2019	2020	2021
Intercept	0.002***	0.007**	0.011*	0.002***	0.000***	0.000***
	(0.777)	(2.178)	(2.640)	(1.870)	(0.609)	(0.835)
race_black	1.439***	1.273***	1.260***	1.221***	1.171***	1.110***
	(0.045)	(0.039)	(0.035)	(0.029)	(0.029)	(0.032)
age	1.181*	1.069	1.066	1.247	1.592***	1.669***
	(0.067)	(0.197)	(0.232)	(0.047)	(0.047)	(0.064)
age2	0.999	1.001	1.001	1.000	0.995***	0.994***
	(0.001)	(0.004)	(0.005)	(0.003)	(0.001)	(0.001)
female	1.544***	1.355***	1.237***	1.248***	1.291***	1.237***
	(0.048)	(0.041)	(0.035)	(0.030)	(0.030)	(0.029)
work_and_study	0.848***	0.870***	0.974	0.974	1.270***	1.338***
	(0.049)	(0.043)	(0.037)	(0.031)	(0.031)	(0.030)
public_high_school	3.297***	2.886***	2.702***	2.231***	2.270***	2.607***
	(0.070)	(0.057)	(0.049)	(0.044)	(0.037)	(0.035)
financing	0.438***	0.570***	0.573***	0.584***	1.751***	1.456***
	(0.050)	(0.041)	(0.036)	(0.030)	(0.030)	(0.031)
affirmative_action	0.060***	0.000***	0.220	0.030	0.053***	0.030***
	(1.007)	(0.187)	(0.200)	(0.167)	(0.172)	(0.172)
N Obs	61841	67991	68431	64365	57903	52361
Control Mean	0.094	0.115	0.151	0.193	0.264	0.352

Note: The coefficients reported in the table represent *odds ratios*. Odds ratios (OR) indicate the relative likelihood of being enrolled in distance education compared to in-person education, given the presence of a specific characteristic. An OR greater than 1 suggests that the characteristic increases the likelihood of distance education enrollment, while an OR less than 1 indicates a decreased likelihood. Standard errors are reported in parentheses and are **robust** to heteroscedasticity. Statistical significance is indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

5.2 Impact of Distance Education Expansion on Enrollment Trends

This section examines how the expansion of distance education (DE) has influenced higher education enrollment trends using the Linear Probability Model (LPM). We track students from cohort 5 (who took the 9th-grade SAEB/Prova Brasil exam in 2011) and cohort 7 (who took the exam in 2013). In this model, Year 1 represents the first year students are expected to be in higher education, assuming continuous academic progression. For cohort 5, Year 1 corresponds to 2015, while for cohort 7, Year 1 is 2017. This distinction allows us to assess how the increased availability of DE programs influenced enrollment decisions over five years.

A key difference between the two groups is their level of exposure to distance education opportunities. cohort 5 had limited access to DE, as large-scale expansion only accelerated after 2017. In contrast, cohort 7 experienced a period of rapid DE growth, which allows us to assess whether the increased supply of DE programs significantly affected enrollment, particularly among students in lower performance percentiles.

For students in the 0–25 percentile range, the evolution of DE enrollment shows a clear contrast between cohorts. In cohort 5, DE enrollment was relatively low, starting at 2% in Year 1 and reaching only 12% by Year 5. However, cohort 7 exhibited a much steeper increase, with DE participation rising from 4% in Year 1 to 24% in Year 5. Meanwhile, in-person enrollment remained relatively stable at around 20% for both cohorts. This pattern suggests that the expansion of DE particularly benefited students with weaker academic performance, making higher education more accessible to them.

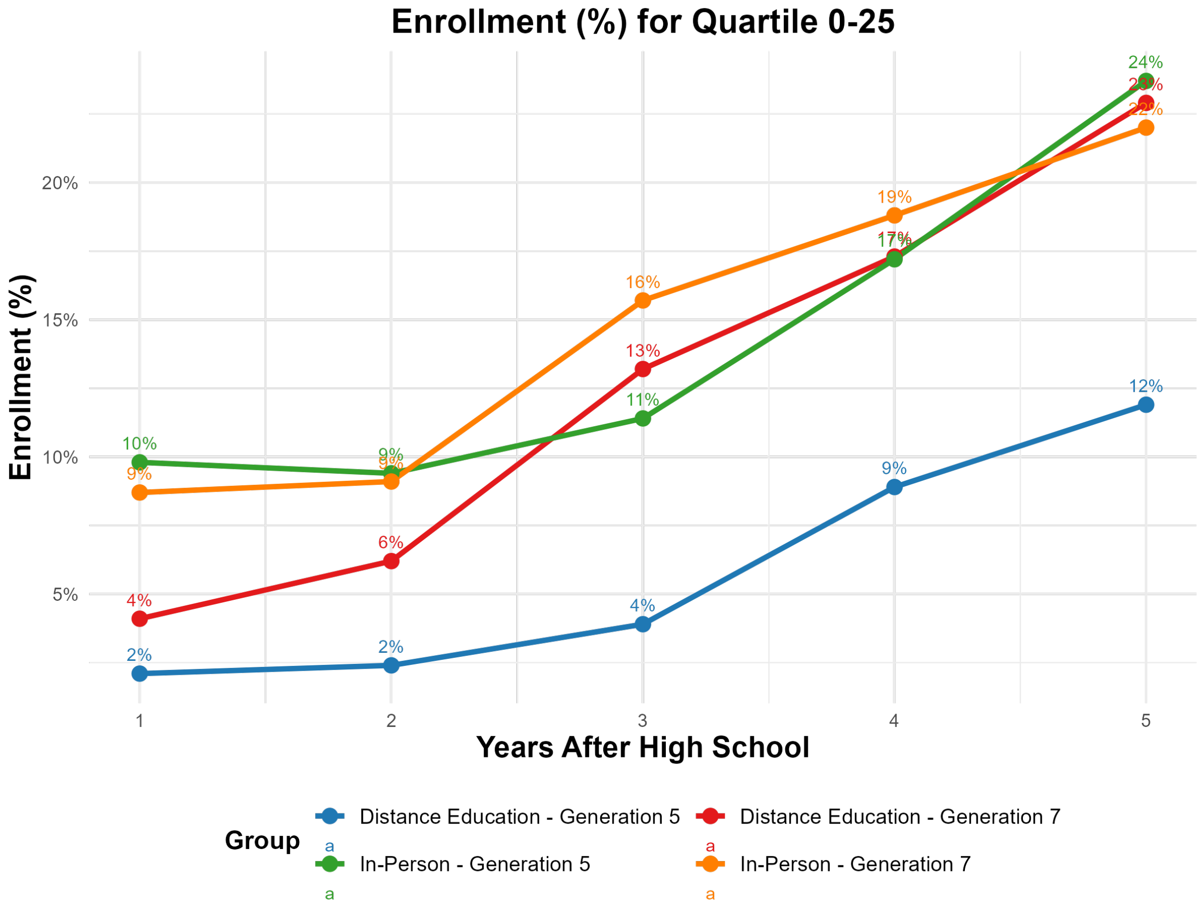

Figure 13: Enrollment (%) for Quartile 0–25.

Note: This figure presents the Control Mean from the five regressions (one per year) estimated for students in the 0–25 percentile range. The values represent the percentage of students enrolled in distance education or in-person education, where the dependent variable takes the value 1 if the student is enrolled and 0 otherwise. Full regression results are provided in the appendix.

A similar pattern emerges in the 25–50 percentile range, where cohort 5 showed a slower increase in DE enrollment, from 5% to 14% over five years, while cohort 7 saw a stronger growth trajectory, rising from 6% to 19%. Notably, in-person enrollment for this quartile also increased, moving from 14% to 20%, reinforcing the idea that DE is not substituting in-person education but rather expanding overall access to higher education.

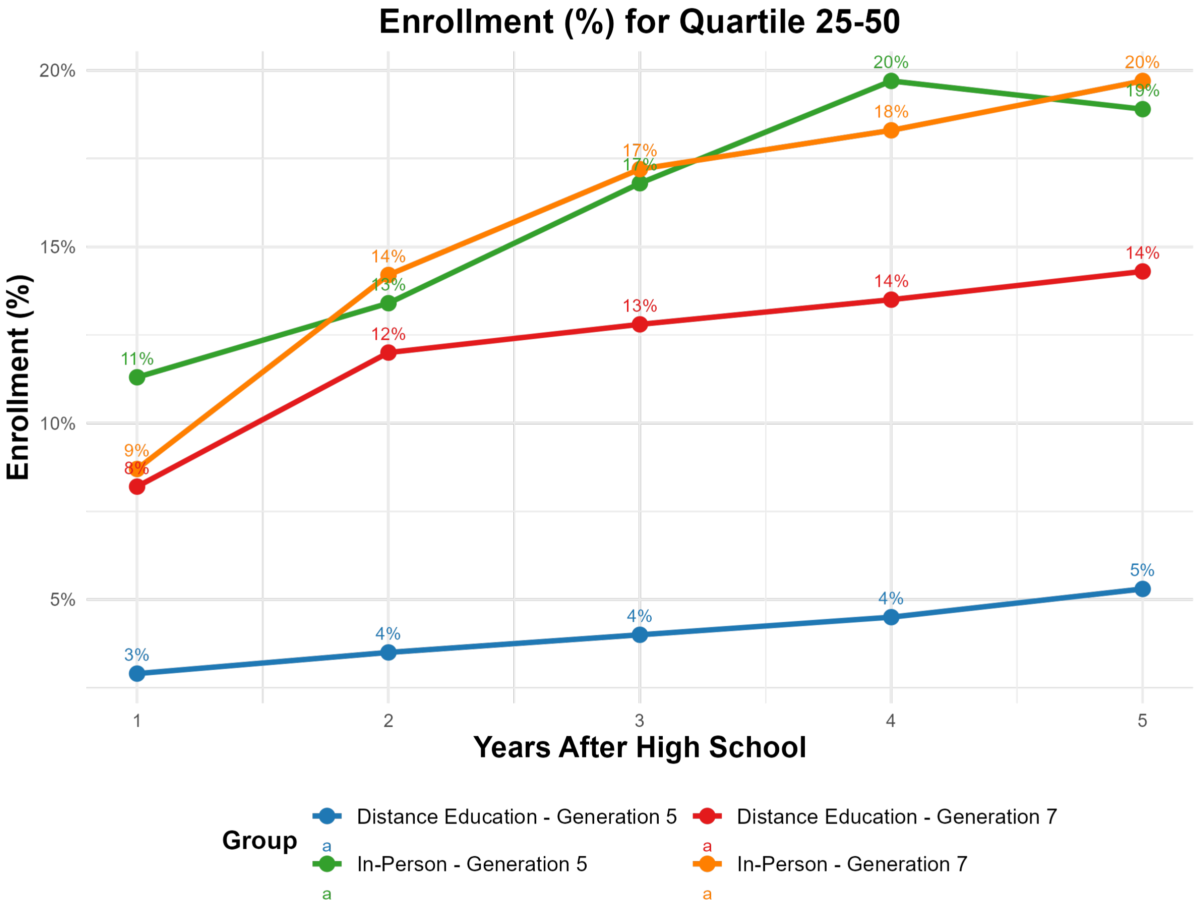

Figure 14: Enrollment (%) for Quartile 25–50.

Note: Similar to Figure 13, this figure shows the Control Mean for students in the 25–50 percentile range, based on the dependent variable, which is 1 if the student is enrolled and 0 otherwise. These values are derived from the five regressions estimated for each year after high school. See the appendix for full regression results.

Among mid-performing students (50–75 percentile), the impact of DE expansion was more moderate. In cohort 5, DE enrollment increased from 8% to 11%, while in cohort 7, it rose from 9% to 17%. However, the most striking trend in this group was the growth of in-person enrollment, which jumped from 30% to nearly 39% in cohort 7. This suggests that while DE options became more widely available, mid-performing students still showed a strong preference for traditional, in-person education.

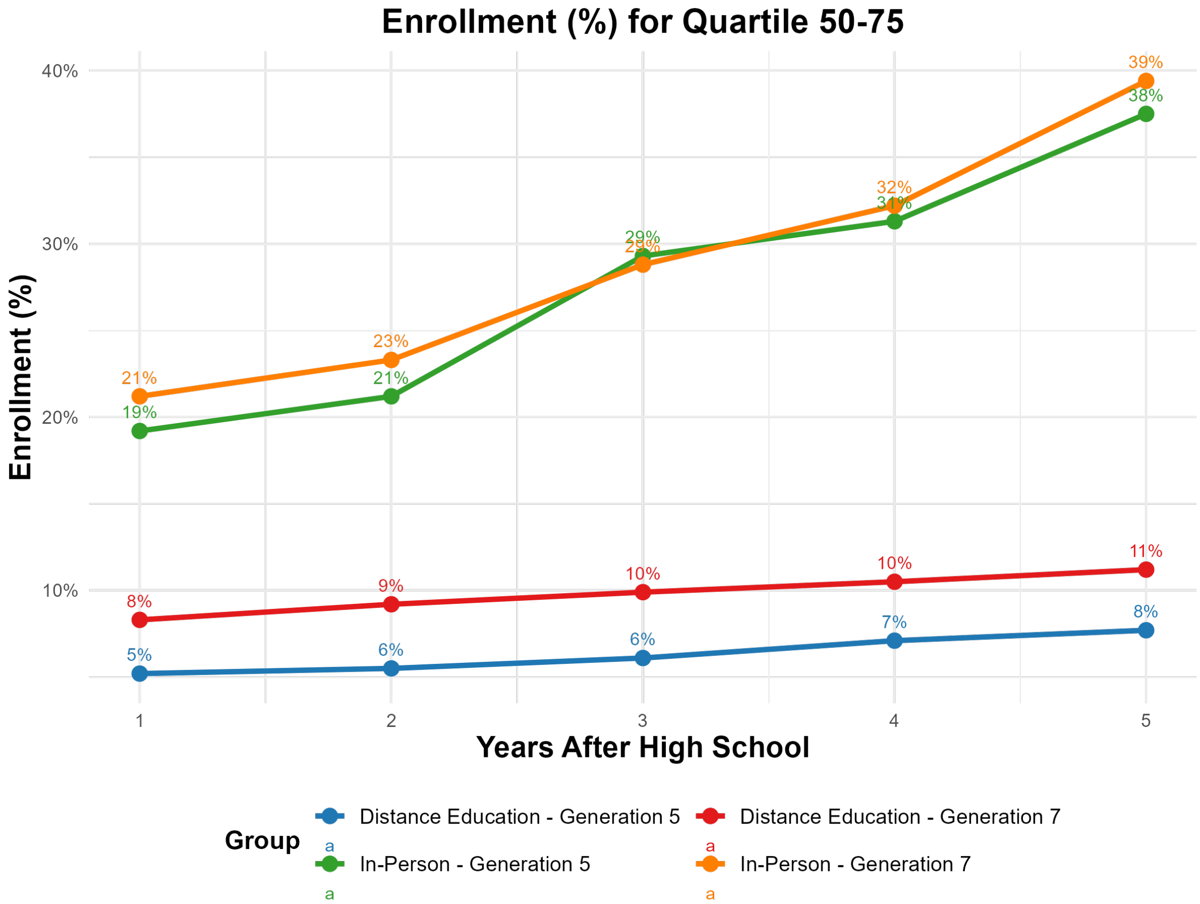

Figure 15: Enrollment (%) for Quartile 50–75.

Note: This figure displays the Control Mean for students in the 50–75 percentile range, representing the percentage of students enrolled in distance or in-person education, where the dependent variable equals 1 if the student is enrolled and 0 otherwise. The appendix contains the full regression tables.

Finally, the highest-performing students (75–100 percentile) displayed minimal change in DE enrollment, with rates remaining between 2–4% across both cohorts. In contrast, in-person enrollment remained dominant, with a slight increase from 42% to 44%. This confirms that DE expansion had little effect on students in the top quartiles, who continued to prioritize traditional education pathways.

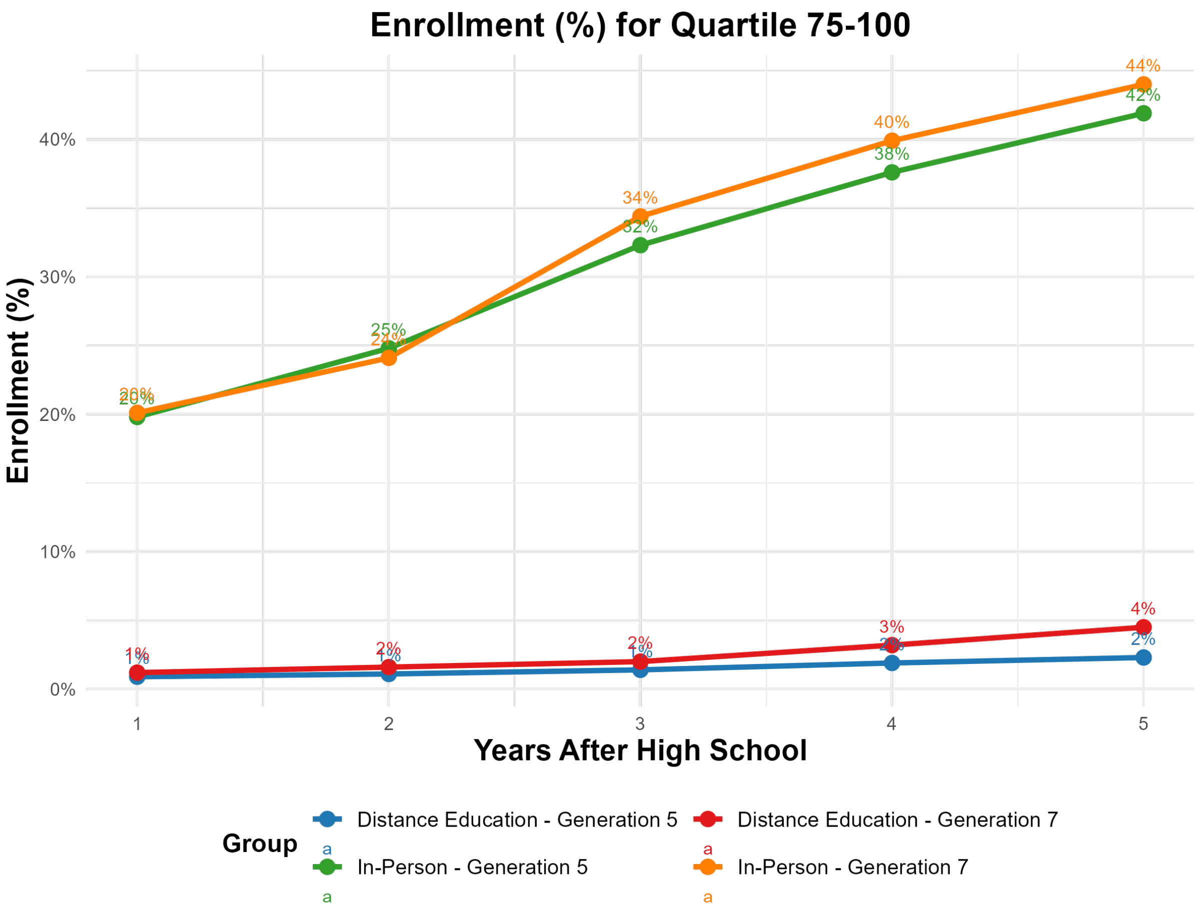

Figure 16: Enrollment (%) for Quartile 75–100.

Note: The values in this figure correspond to the Control Mean for students in the 75–100 percentile range, where the dependent variable takes the value 1 if the student is enrolled and 0 otherwise. These values come from the five regressions estimated for each year after high school. Complete regression details are available in the appendix.

These results highlight three key takeaways. First, DE enrollment grew significantly among lower-performing students (0–50 percentile), especially in cohort 7, who had greater access to DE programs. Second, in-person enrollment remained stable or even increased across all quartiles, indicating that DE is not replacing traditional education but rather serving as an alternative path for students who might not have enrolled otherwise. Lastly, higher-performing students (75–100 percentile) showed little change in DE participation, confirming that DE primarily serves students facing greater educational barriers.

Taken together, these findings support the argument that distance education acts as a complementary pathway rather than a substitute for in-person education. The expansion of DE has allowed a broader segment of the population—particularly lower-performing students—to access higher education, but without significantly diverting students from in-person institutions.

6 Conclusion

This study contributes to the literature on distance education (DE) in Brazil by offering a comprehensive analysis of the evolving profiles of DE students and their increasing access to higher education, particularly for those in the lower percentiles of the Prova Brasil. Our findings underscore that DE has significantly expanded access to higher education for students who might not have otherwise enrolled, especially individuals with weaker academic backgrounds, such as those with lower scores in Portuguese and Mathematics in early schooling years.

In line with literature on the subject, such as the study by (Latanich, Nonis, and Hudson 2001), which highlights how distance education serves as a strategy for individuals to optimize their time and resources, our research shows that DE in Brazil is also a flexible alternative for those balancing work, family, and academic commitments. This demographic profile, characterized by older students, predominantly female learners, and those more likely to be employed full-time, is similar to trends observed in the United States. The flexibility offered by DE has enabled these students to reconcile professional, personal, and educational responsibilities, making higher education more accessible to a diverse group of individuals.

While DE has grown rapidly, particularly among students with lower academic performance, it has not displaced traditional in-person education. Instead, it has complemented the existing system, providing an alternative pathway that increases overall access to higher education. This finding reflects DE's role as a tool for social inclusion, rather than as a substitute for in-person learning.

Looking forward, future research could further explore the long-term impacts of DE on student outcomes, particularly in terms of labor market integration and educational attainment. Additionally, examining the challenges posed by the quality of education in rapidly expanding DE programs could provide valuable insights into how to improve and regulate this growing sector. There is also potential for further expansion of DE programs to address the educational needs of marginalized groups, ensuring that the growth of distance education continues to promote equity and inclusivity in higher education.

By enhancing our understanding of the evolving profile of DE students, this research lays the groundwork for further studies on the broader impacts of DE on educational and social mobility in Brazil.

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A Appendix

A.1 Percentile – 0–25

Table 5: Impact of the Expansion of Distance Education on Access to Higher Education in the First Year After High School (PB_Percentile_Rank 0–25, cohorts 5 and 7)

	Distance Education vs. All		**In-Person vs. All**	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Percentile_Rank	0.002	0.015	0.004	0.008
	(0.004)	(0.008)	(0.005)	(0.008)
Race (Binary)	0.072**	0.085*	-0.084	-0.095*
	(0.074)	(0.099)	(0.078)	(0.103)
Age	0.043*	0.058**	-0.043**	-0.060*
	(0.015)	(0.025)	(0.016)	(0.026)
Female	0.141	0.182*	-0.134	-0.170
	(0.055)	(0.084)	(0.056)	(0.086)
Public School	0.223	0.153*	-0.232	-0.163*
	(0.060)	(0.075)	(0.065)	(0.079)
Work & Study	-0.097	-0.120	0.085	0.100
	(0.070)	(0.150)	(0.075)	(0.155)
Constant	-0.257	-0.182	0.303	0.217
	(0.830)	(1.070)	(0.840)	(1.090)
Observations	6,187	4,620	6,187	4,620
R^2	0.092	0.073	0.113	0.083
Control Mean	0.021	0.041	0.098	0.087

Notes: Robust standard errors in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

PB_Percentile_Rank refers to the student's continuous percentile rank in the Prova Brasil exam, with values ranging from 0 (lowest performance) to 25 (highest within this range). This variable is used to identify students' performance, with the focus on the lowest performing students (PB_Percentile_Rank 0-25).

The final sample includes individuals within this percentile range tracked in their first year after completing high school, regardless of whether or not they enrolled in higher education.

Sample attrition occurred primarily due to (i) high school dropout, (ii) the lack of a valid (or matched) CPF in administrative records, and (iii) missing information on key variables, which reduced the initial pool of students to those shown in this table.

Table 6: Impact of the Expansion of Distance Education on Access to Higher Education in the Second Year After High School (PB_Quartile–25, cohort 5 and 7)

	Distance Education vs. All		**In-Person vs. All**	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Percentile_Rank	0.003	0.027*	0.005	-0.017
	(0.005)	(0.010)	(0.006)	(0.010)
Race (Binary)	0.075**	0.1252**	-0.085**	-0.139***
	(0.028)	(0.032)	(0.029)	(0.034)
Age	0.048*	0.085*	-0.043*	-0.093*
	(0.019)	(0.022)	(0.016)	(0.022)
Female	0.143**	0.252**	-0.140*	-0.2258*
	(0.056)	(0.063)	(0.057)	(0.059)
Public School	0.221	0.354**	-0.235	-0.255*
	(0.061)	(0.076)	(0.066)	(0.073)
Work & Study	-0.103	-0.058	0.092	0.135
	(0.071)	(0.081)	(0.076)	(0.086)
Constant	-0.254	-0.202	0.303	0.285
	(0.835)	(1.105)	(0.845)	(1.125)
Observations	6,187	4,620	6,187	4,620
$\mathbf{R^2}$	0.096	0.094	0.117	0.099
Control Mean	0.024	0.062	0.094	0.091

Notes: Robust standard errors in parentheses. Significance levels: *** 1%, ** 5%, * 10%.
PB_Quartile_0–25 indicates the student's percentile rank in the Prova Brasil exam, ranging from 0 (lowest performance) to 25 (highest within this quartile). This table focuses exclusively on students within the PB_Quartile_0–25.
The final sample includes individuals in this quartile tracked in their second year after completing high school, regardless of whether or not they enrolled in higher education.
Sample attrition occurred primarily due to (i) high school dropout, (ii) the lack of a valid (or matched) CPF in administrative records, and (iii) missing information on key variables, which reduced the initial pool of students to those shown in this table.

Table 7: Impact of the Expansion of Distance Education on Access to Higher Education in the Third Year After High School (PB_Quartile_0–25, cohort 5 and 7)

	Distance Education vs. All		**In-Person vs. All**	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Percentile_Rank	0.008	0.035**	-0.016	-0.022
	(0.005)	(0.011)	(0.006)	(0.012)
Race (Binary)	0.081*	0.142**	-0.090**	-0.153*
	(0.029)	(0.035)	(0.030)	(0.036)
Age	0.051**	0.096***	-0.042***	-0.106***
	(0.020)	(0.024)	(0.017)	(0.024)
Female	0.155*	0.272**	-0.146***	-0.241***
	(0.057)	(0.065)	(0.058)	(0.062)
Public School	0.230*	0.381**	-0.243*	-0.278*
	(0.062)	(0.078)	(0.067)	(0.075)
Work & Study	-0.113	-0.061	0.096	0.141
	(0.072)	(0.083)	(0.077)	(0.088)
Constant	-0.261	-0.219	0.310	0.297
	(0.840)	(1.110)	(0.850)	(1.130)
Observations	6,187	4,620	6,187	4,620
$\mathbf{R^2}$	0.100	0.102	0.121	0.105
Control Mean	0.039	0.132	0.114	0.157

Notes: Robust standard errors in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

PB_Quartile_0–25 indicates the student's percentile rank in the SAEB exam (renamed from Prova Brasil), ranging from 0 (lowest performance) to 25.

The final sample includes individuals tracked in their third year after high school.

Other notes consistent with previous tables (attrition reasons, quartile focus, etc.).

Table 8: Impact of the Expansion of Distance Education on Access to Higher Education in the Fourth Year After High School (PB_Quartile_0–25, cohort 5 and 7)

	Distance Education vs. All		**In-Person vs. All**	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Percentile_Rank	0.012*	0.040***	-0.019	-0.026
	(0.006)	(0.012)	(0.007)	(0.013)
Race (Binary)	0.086**	0.143***	-0.098*	-0.151*
	(0.032)	(0.036)	(0.033)	(0.037)
Age	0.052**	0.106*	-0.051*	-0.111**
	(0.021)	(0.026)	(0.018)	(0.027)
Female	0.168*	0.276**	-0.156	-0.258
	(0.058)	(0.065)	(0.059)	(0.064)
Public School	0.247**	0.386*	-0.250**	-0.276**
	(0.064)	(0.081)	(0.069)	(0.078)
Work & Study	-0.116	-0.071	0.096	0.142**
	(0.074)	(0.085)	(0.079)	(0.090)
Constant	-0.266	-0.221	0.321	0.301
	(0.855)	(1.130)	(0.865)	(1.150)
Observations	6,187	4,620	6,187	4,620
$\mathbf{R^2}$	0.105	0.110	0.125	0.107
Control Mean	0.089	0.173	0.172	0.188

Notes: Robust standard errors in parentheses. Significance levels: *** 1%, ** 5%, * 10%.
This table focuses on the third year after completing high school, highlighting the continued growth of Distance Education enrollment among cohort 7 students.

Table 9: Impact of the Expansion of Distance Education on Access to Higher Education in the Fifth Year After High School (PB_Quartile_0–25, cohort 5 and 7)

	Distance Education vs. All		**In-Person vs. All**	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Percentile_Rank	0.018**	0.051***	-0.011	-0.031
	(0.007)	(0.014)	(0.008)	(0.015)
Race (Binary)	0.096*	0.161*	-0.096*	-0.171
	(0.034)	(0.040)	(0.035)	(0.042)
Age	0.064**	0.114*	-0.059	-0.126*
	(0.022)	(0.028)	(0.019)	(0.030)
Female	0.176***	0.304***	-0.160***	-0.271***
	(0.060)	(0.070)	(0.062)	(0.068)
Public School	0.265***	0.423***	-0.272**	-0.301*
	(0.068)	(0.085)	(0.072)	(0.082)
Work & Study	-0.121	-0.085	0.106	0.156
	(0.076)	(0.090)	(0.081)	(0.095)
Constant	-0.276	-0.242	0.331	0.316
	(0.870)	(1.150)	(0.880)	(1.170)
Observations	6,187	4,620	6,187	4,620
$\mathbf{R^2}$	0.110	0.120	0.130	0.115
Control Mean	0.119	0.229	0.237	0.220

Notes: Robust standard errors in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

In the fifth year after completing high school, the impact of Distance Education (EaD) continues to grow, particularly for cohort 7 students, reflecting the sustained effect of the 2017 EaD expansion policies.

PB_Quartile_0–25 refers to the lowest quartile of performance in the Prova Brasil exam, highlighting how the accessibility of EaD has increased higher education enrollment opportunities for this group over time.

A.2 Percentile – 25–50

Table 10: Impact of the Expansion of Distance Education on Access to Higher Education in the First Year After High School (PB_Quartile_25-50, cohorts 5 and 7)

	Distance Education vs. All		In-Person vs. All	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Quartile_25-50	-0.013	-0.011	0.024	0.027
	(0.006)	(0.004)	(0.007)	(0.006)
Race (Binary)	0.062	0.078	-0.069*	-0.081**
	(0.073)	(0.088)	(0.072)	(0.091)
Age	0.042*	0.056*	-0.036	-0.059***
	(0.016)	(0.027)	(0.015)	(0.026)
Female	0.134*	0.172*	-0.126	-0.164
	(0.054)	(0.086)	(0.055)	(0.087)
Public School	0.210**	0.156*	-0.213**	-0.159**
	(0.061)	(0.076)	(0.064)	(0.078)
Work & Study	-0.087	-0.110	0.085	0.097
	(0.072)	(0.148)	(0.075)	(0.155)
Constant	-0.233	-0.167	0.289	0.202
	(0.823)	(1.055)	(0.827)	(1.078)
Observations	7,200	5,300	7,200	5,300
R^2	0.085	0.068	0.105	0.078
Control Mean	0.029	0.082	0.113	0.102

Notes: Robust standard errors in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

PB_Quartile_25-50 refers to the student's performance in the 25-50 percentile of the Prova Brasil.

Students with better performance within this group have lower probability of entering Distance Education (negative coefficients), but higher probability of entering In-Person Education (positive coefficients).

The sample includes only students in this quartile, followed for 5 years after high school. Attrition is similar to Table 1.

Table 11: Impact of the Expansion of Distance Education on Access to Higher Education in the Second Year After High School (PB_Quartile_25-50, cohorts 5 and 7)

	Distance Education vs. All		In-Person vs. All	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Quartile_25-50	-0.009	-0.002**	0.017*	0.032*
	(0.006)	(0.004)	(0.005)	(0.006)
Race (Binary)	0.062*	0.076*	-0.068*	-0.088**
	(0.071)	(0.090)	(0.073)	(0.094)
Age	0.038*	0.054*	-0.036	-0.061***
	(0.015)	(0.026)	(0.016)	(0.027)
Female	0.132*	0.168*	-0.120	-0.162
	(0.056)	(0.087)	(0.057)	(0.088)
Public School	0.208**	0.152*	-0.215**	-0.162**
	(0.060)	(0.077)	(0.064)	(0.079)
Work & Study	-0.089	-0.111	0.082	0.097
	(0.073)	(0.149)	(0.076)	(0.155)
Constant	-0.225	-0.168	0.284	0.198
	(0.823)	(1.056)	(0.827)	(1.080)
Observations	7,200	5,300	7,200	5,300
R^2	0.089	0.072	0.112	0.085
Control Mean	0.035	0.120	0.134	0.142

Notes: Robust standard errors in parentheses. Significance levels: *** 1%, ** 5%, * 10%.
PB_Quartile_25-50 refers to the student's performance in the 25-50 percentile of the Prova Brasil.
Students with better performance within this group have lower probability of entering Distance Education (negative coefficients), but higher probability of entering In-Person Education (positive coefficients).
The sample includes only students in this quartile, followed for 5 years after high school. Attrition is similar to Table 1.

Table 12: Impact of the Expansion of Distance Education on Access to Higher Education in the Third Year After High School (PB_Quartile_25-50, cohorts 5 and 7)

	Distance Education vs. All		**In-Person vs. All**	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Quartile_25-50	-0.012*	0.0028**	0.022***	0.037***
	(0.005)	(0.006)	(0.003)	(0.005)
Race (Binary)	0.067*	0.085**	-0.072*	-0.093**
	(0.065)	(0.078)	(0.067)	(0.090)
Age	0.038**	0.055*	-0.034*	-0.062***
	(0.012)	(0.025)	(0.014)	(0.027)
Female	0.140*	0.185**	-0.138	-0.172*
	(0.050)	(0.075)	(0.051)	(0.080)
Public School	0.212***	0.158**	-0.222***	-0.167**
	(0.055)	(0.070)	(0.060)	(0.075)
Work & Study	-0.092	-0.118	0.084	0.107
	(0.072)	(0.149)	(0.075)	(0.150)
Constant	-0.250	-0.185	0.302	0.215
	(0.800)	(1.100)	(0.810)	(1.090)
Observations	7,200	5,300	7,200	5,300
R^2	0.090	0.075	0.115	0.090
Control Mean	0.040	0.128	0.168	0.172

Notes: Robust standard errors in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

The sample includes only students tracked for 3 years after high school. Attrition is similar to previous years.

Table 13: Impact of the Expansion of Distance Education on Access to Higher Education in the Fourth Year After High School (PB_Quartile_25-50, cohorts 5 and 7)

	Distance Education vs. All		**In-Person vs. All**	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Quartile_25-50	-0.014**	0.029***	0.026***	0.042***
	(0.006)	(0.007)	(0.005)	(0.007)
Race (Binary)	0.071*	0.087**	-0.076*	-0.097***
	(0.062)	(0.083)	(0.064)	(0.089)
Age	0.041**	0.062**	-0.037**	-0.067***
	(0.012)	(0.027)	(0.015)	(0.027)
Female	0.139**	0.192**	-0.146*	-0.182**
	(0.051)	(0.077)	(0.053)	(0.082)
Public School	0.223***	0.163**	-0.233***	-0.172**
	(0.058)	(0.073)	(0.063)	(0.078)
Work & Study	-0.098	-0.134	0.086	0.113
	(0.070)	(0.151)	(0.073)	(0.153)
Constant	-0.263	-0.191	0.312	0.223
	(0.810)	(1.090)	(0.820)	(1.110)
Observations	7,200	5,300	7,200	5,300
R^2	0.096	0.081	0.121	0.096
Control Mean	0.045	0.135	0.197	0.183

Notes: Coefficients for Distance Education in Quartile 25-50 are negative and significant in cohort 7 (-0.029***), while in-person education shows a positive and increasing effect (0.042***). This pattern is consistent with the hypothesis that Distance Education did not replace in-person education for medium-performing students.

Table 14: Impact of the Expansion of Distance Education on Access to Higher Education in the Fifth Year After High School (PB_Quartile_25-50, cohorts 5 and 7)

	Distance Education vs. All		**In-Person vs. All**	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Quartile_25-50	-0.016***	0.036***	0.032***	0.047***
	(0.007)	(0.008)	(0.006)	(0.008)
Race (Binary)	0.078**	0.092***	-0.085**	-0.102***
	(0.061)	(0.083)	(0.064)	(0.088)
Age	0.046***	0.067**	-0.041**	-0.073***
	(0.015)	(0.029)	(0.017)	(0.031)
Female	0.151**	0.201***	-0.156**	-0.191***
	(0.053)	(0.076)	(0.055)	(0.079)
Public School	0.234***	0.174***	-0.245***	-0.182***
	(0.060)	(0.075)	(0.065)	(0.078)
Work & Study	-0.101	-0.141	0.092	0.125
	(0.072)	(0.156)	(0.076)	(0.161)
Constant	-0.275	-0.205	0.323	0.235
	(0.830)	(1.110)	(0.840)	(1.130)
Observations	7,200	5,300	7,200	5,300
R^2	0.102	0.087	0.129	0.103
Control Mean	0.053	0.143	0.189	0.197

Notes: Cumulative effect: students in the 25-50 percentile in cohort 7 have a -3.6 p.p. probability for Distance Education and +4.7 p.p. for In-Person Education. This confirms that Distance Education did not compete with in-person education for medium-performing students.

A.3 Percentile – 50 – 75

Table 15: Impact of the Expansion of Distance Education on Access to Higher Education in the 50-75 Percentile First Year After High School (PB_Quartile_50-75, cohorts 5 and 7)

	Distance Education vs. All		In-Person vs. All	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Quartile_50-75	-0.019	-0.008	0.033**	0.059**
	(0.011)	(0.012)	(0.006)	(0.009)
Race (Binary)	-0.027	0.032	-0.093**	-0.115***
	(0.074)	(0.093)	(0.081)	(0.098)
Age	0.021*	0.029*	-0.052**	-0.078**
	(0.017)	(0.022)	(0.018)	(0.031)
Female	0.042	0.027	-0.162**	-0.212***
	(0.058)	(0.074)	(0.061)	(0.085)
Public School	0.062	0.074	-0.235	-0.184
	(0.068)	(0.083)	(0.073)	(0.088)
Work & Study	-0.031	0.020	0.127	0.149
	(0.072)	(0.145)	(0.075)	(0.153)
Constant	-0.250	-0.197	0.335	0.253
	(0.810)	(1.076)	(0.822)	(1.101)
Observations	7,188	5,273	7,188	5,273
R^2	0.122	0.087	0.133	0.100
Control Mean	0.052	0.083	0.192	0.197

Notes: Robust standard errors in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

PB_Quartile_50-75: Students with better performance than the 50th percentile have a higher probability of attending In-Person Education, with positive and significant coefficients. For Distance Education, the coefficients are mixed, with no statistical significance.

The sample includes only students in this quartile, tracked for 5 years after high school. Attrition is similar to the previous tables.

Table 16: Impact of the Expansion of Distance Education on Access to Higher Education in the Second Year After High School (PB_Quartile_50-75, cohorts 5 and 7)

	Distance Education vs. All		In-Person vs. All	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Quartile_50-75	-0.016	-0.009	0.039***	0.073***
	(0.009)	(0.008)	(0.006)	(0.009)
Race (Binary)	-0.031	0.039	-0.089**	-0.112***
	(0.071)	(0.092)	(0.080)	(0.099)
Age	0.022*	0.031*	-0.049**	-0.072**
	(0.015)	(0.022)	(0.016)	(0.028)
Female	-0.041	0.028	0.164**	0.221***
	(0.059)	(0.078)	(0.062)	(0.087)
Public School	0.063	-0.079	-0.243	-0.190
	(0.072)	(0.086)	(0.075)	(0.090)
Work & Study	-0.030	0.015	0.124*	0.155**
	(0.073)	(0.145)	(0.078)	(0.158)
Constant	-0.255	-0.202	0.335	0.257
	(0.824)	(1.092)	(0.840)	(1.120)
Observations	7,188	5,273	7,188	5,273
R^2	0.131	0.087	0.133	0.172
Control Mean	0.055	0.092	0.212	0.233

Notes: Robust standard errors in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

PB_Quartile_50-75: Students with performance above the 50th percentile have a higher probability of enrolling in In-Person Education, with positive and significant coefficients. For Distance Education, the coefficients are mixed, with no statistical significance.

The sample includes only students in this quartile, tracked for 2 years after high school.

Table 17: Impact of the Expansion of Distance Education on Access to Higher Education in the Third Year After High School (PB_Quartile_50-75, cohorts 5 and 7)

	Distance Education vs. All		In-Person vs. All	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Quartile_50-75	-0.010*	-0.005*	0.049***	0.099***
	(0.008)	(0.007)	(0.005)	(0.007)
Race (Binary)	0.022	0.025	-0.080	-0.100
	(0.061)	(0.082)	(0.073)	(0.094)
Age	0.012*	0.020*	-0.045**	-0.065**
	(0.014)	(0.020)	(0.014)	(0.026)
Female	-0.030	0.020	-0.150	-0.200
	(0.053)	(0.075)	(0.052)	(0.075)
Public School	0.051	-0.063	0.222	0.170
	(0.055)	(0.073)	(0.059)	(0.074)
Work & Study	-0.024	0.011	0.112*	0.146*
	(0.063)	(0.141)	(0.072)	(0.159)
Constant	-0.242	-0.183	0.327	0.246
	(0.812)	(1.055)	(0.801)	(1.052)
Observations	7,188	5,273	7,188	5,273
R^2	0.122	0.085	0.132	0.111
Control Mean	0.061	0.099	0.293	0.288

Notes: Robust standard errors in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

PB_Quartile_50-75: Alunos com desempenho superior ao percentil 50 têm maior probabilidade de ingressar no presencial, com coeficientes positivos e significativos. Para o EAD, os coeficientes são mistos, sem significância estatística. A amostra considera apenas alunos deste quartil, acompanhados por 3 anos após o ensino médio.

Table 18: Impact of the Expansion of Distance Education on Access to Higher Education in the Fourth Year After High School (PB_Quartile_50-75, cohorts 5 and 7)

	Distance Education vs. All		**In-Person vs. All**	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Quartile_50-75	-0.014*	-0.009*	0.120***	0.112***
	(0.009)	(0.008)	(0.006)	(0.008)
Race (Binary)	-0.028	0.033	-0.085	-0.112
	(0.073)	(0.092)	(0.080)	(0.104)
Age	0.021	0.031	0.049**	0.075**
	(0.016)	(0.022)	(0.018)	(0.031)
Female	-0.034	0.024	0.160	0.218
	(0.055)	(0.077)	(0.060)	(0.090)
Public School	0.060	-0.070	0.235	0.185
	(0.072)	(0.095)	(0.078)	(0.098)
Work & Study	-0.030	0.012	0.122*	0.153**
	(0.061)	(0.150)	(0.072)	(0.160)
Constant	-0.275	-0.210	0.330	0.245
	(0.843)	(1.122)	(0.854)	(1.130)
Observations	7,188	5,273	7,188	5,273
R^2	0.235	0.140	0.205	0.130
Control Mean	0.071	0.105	0.313	0.322

Notes: Robust standard errors in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

PB_Quartile_50-75: Students with performance above the 50th percentile have a higher probability of enrolling in In-Person Education, with positive and significant coefficients. For Distance Education, the coefficients are mixed, with no statistical significance.

The sample includes only students in this quartile, tracked for 4 years after high school.

Table 19: Impact of the Expansion of Distance Education on Access to Higher Education in the Fifth Year After High School (PB_Quartile_50-75, cohorts 5 and 7)

	Distance Education vs. All		**In-Person vs. All**	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Quartile_50-75	-0.014*	-0.009*	0.095***	0.092***
	(0.008)	(0.007)	(0.006)	(0.008)
Race (Binary)	0.022	0.031	-0.083	-0.108
	(0.062)	(0.084)	(0.072)	(0.092)
Age	0.015	0.022	0.048*	0.073*
	(0.013)	(0.019)	(0.015)	(0.027)
Female	-0.028	0.022	0.158	0.212
	(0.053)	(0.072)	(0.056)	(0.089)
Public School	0.057	-0.065	0.234	0.186
	(0.064)	(0.078)	(0.067)	(0.085)
Work & Study	-0.023	0.012	0.125**	0.158**
	(0.059)	(0.137)	(0.070)	(0.145)
Constant	-0.259	-0.191	0.335	0.247
	(0.803)	(1.050)	(0.810)	(1.100)
Observations	7,188	5,273	7,188	5,273
R^2	0.237	0.140	0.317	0.207
Control Mean	0.077	0.112	0.375	0.394

Notes: Robust standard errors in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

PB_Quartile_50-75: Students with performance above the 50th percentile have a higher probability of enrolling in In-Person Education, with positive and significant coefficients. For Distance Education, the coefficients are mixed, with no statistical significance.

The sample includes only students in this quartile, tracked for 5 years after high school (post-graduation).

A.4 Percentile – 75 – 100

Table 20: Impact of the Expansion of Distance Education on Access to Higher Education in the 50-75 Percentile First Year After High School (PB_Quartile_75-100, cohorts 5 and 7)

	Distance Education vs. All		**In-Person vs. All**	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Quartile_75-100	-0.018	-0.007	0.036*	0.059*
	(0.011)	(0.012)	(0.005)	(0.009)
Race (Binary)	-0.026	0.037	0.085	0.114
	(0.074)	(0.093)	(0.080)	(0.091)
Age	0.022*	0.027*	-0.047**	-0.071**
	(0.016)	(0.021)	(0.017)	(0.027)
Female	0.031	0.021	-0.159	-0.205
	(0.057)	(0.073)	(0.061)	(0.081)
Public School	0.061	0.080	-0.242	-0.192
	(0.065)	(0.082)	(0.069)	(0.086)
Work & Study	-0.024	0.013	0.126*	0.155**
	(0.063)	(0.142)	(0.070)	(0.157)
Constant	-0.242	-0.180	0.335	0.270
	(0.810)	(1.052)	(0.818)	(1.120)
Observations	7,482	5,535	7,482	5,535
R^2	0.123	0.084	0.121	0.122
Control Mean	0.009	0.012	0.198	0.201

Robust standard errors in parentheses. Significance levels: *** 1%, ** 5%, * 10%.

Sample includes only students in this percentile tracked in their first year after high school.

Table 21: Impact of the Expansion of Distance Education on Access to Higher Education in the Second Year After High School (PB_Quartile_75-100, cohorts 5 and 7)

	Distance Education vs. All		In-Person vs. All	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Quartile_75-100	-0.022**	-0.030**	0.055**	0.075**
	(0.007)	(0.008)	(0.007)	(0.008)
Race (Binary)	-0.040	0.035	0.112	0.143
	(0.057)	(0.077)	(0.062)	(0.082)
Age	0.018	0.025	0.061	0.083
	(0.013)	(0.019)	(0.013)	(0.021)
Female	0.045	0.028	0.187	0.222
	(0.046)	(0.066)	(0.049)	(0.071)
Public School	-0.087	-0.126	0.255	0.213
	(0.049)	(0.061)	(0.053)	(0.066)
Work & Study	-0.035	-0.015	0.132**	0.161**
	(0.056)	(0.132)	(0.066)	(0.142)
Constant	-0.273	-0.202	0.373	0.283
	(0.764)	(1.012)	(0.772)	(1.033)
Observations	7,482	5,535	7,482	5,535
R^2	0.132	0.124	0.133	0.115
Control Mean	0.011	0.016	0.248	0.241

Cumulative effect: -3.0 p.p. in Distance Education and +7.5 p.p. in In-Person education for cohort 7.

Table 22: Impact of the Expansion of Distance Education on Access to Higher Education in the Third Year After High School (PB_Quartile_75-100, cohorts 5 and 7)

	Distance Education vs. All		**In-Person vs. All**	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Quartile_75-100	-0.027***	-0.037***	0.072***	0.091***
	(0.007)	(0.008)	(0.006)	(0.008)
Race (Binary)	-0.048	0.045	0.134	0.167
	(0.061)	(0.082)	(0.068)	(0.090)
Age	0.023	0.032	-0.068	-0.089
	(0.015)	(0.019)	(0.016)	(0.022)
Female	-0.052	0.033	0.184	0.224
	(0.052)	(0.073)	(0.056)	(0.073)
Public School	-0.092	-0.126	0.264	0.225
	(0.051)	(0.062)	(0.056)	(0.073)
Works and Studies	-0.042	-0.027	0.145**	0.175**
	(0.057)	(0.122)	(0.062)	(0.134)
Constant	-0.285	-0.215	0.398	0.310
	(0.762)	(1.026)	(0.774)	(1.033)
Observations	7,482	5,535	7,482	5,535
R^2	0.145	0.131	0.122	0.135
Control Mean	0.014	0.020	0.323	0.344

Final results: -3.7 p.p. in Distance Education and +9.1 p.p. in In-Person education for cohort 7.

Table 23: Impact of the Expansion of Distance Education on Access to Higher Education in the Fourth Year After High School (PB_Quartile_75-100, cohorts 5 and 7)

	Distance Education vs. All		**In-Person vs. All**	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Quartile_75-100	-0.027***	-0.038***	0.073***	0.093***
	(0.008)	(0.009)	(0.007)	(0.009)
Race (Binary)	-0.049	0.045	0.137	0.160
	(0.063)	(0.085)	(0.073)	(0.091)
Age	0.027	0.037	-0.072	-0.091
	(0.016)	(0.020)	(0.017)	(0.026)
Female	-0.062	0.038	0.195***	0.235***
	(0.057)	(0.078)	(0.060)	(0.080)
Public School	-0.097	-0.131	0.282	0.241
	(0.056)	(0.071)	(0.061)	(0.076)
Works and Studies	-0.047	-0.038	0.153**	0.183**
	(0.061)	(0.133)	(0.065)	(0.143)
Constant	-0.303	-0.247	0.410	0.320
	(0.775)	(1.026)	(0.783)	(1.045)
Observations	7,482	5,535	7,482	5,535
R^2	0.132	0.161	0.129	0.149
Control Mean	0.019	0.032	0.376	0.399

Final results: -3.8 p.p. in Distance Education and +9.3 p.p. in In-Person education for cohort 7.

Table 24: Impact of the Expansion of Distance Education on Access to Higher Education in the Fifth Year After High School (PB_Quartile_75-100, cohorts 5 and 7)

	Distance Education vs. All		**In-Person vs. All**	
Covariate	**cohort 5**	**cohort 7**	**cohort 5**	**cohort 7**
PB_Quartile_75-100	-0.032***	-0.042***	0.078***	0.099***
	(0.009)	(0.017)	(0.007)	(0.009)
Race (Binary)	-0.054	0.048	0.142	0.172
	(0.069)	(0.084)	(0.065)	(0.085)
Age	0.027*	0.036*	-0.078	-0.098
	(0.015)	(0.024)	(0.015)	(0.022)
Female	0.062	0.023	-0.215	-0.265
	(0.051)	(0.073)	(0.053)	(0.074)
Public School	0.113	0.151	-0.288	-0.240
	(0.053)	(0.062)	(0.055)	(0.068)
Work & Study	0.048	0.022	0.163**	0.195**
	(0.060)	(0.136)	(0.069)	(0.148)
Constant	-0.305	-0.230	0.420	0.330
	(0.780)	(1.030)	(0.790)	(1.050)
Observations	7,482	5,533	7,482	5,535
R^2	0.122	0.147	0.138	0.190
Control Mean	0.023	0.045	0.419	0.440

Final results: -4.2 p.p. in Distance Education and +9.9 p.p. in In-Person education for cohort 7.