

# Labor market conditions and college graduation<sup>\*</sup>

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## Abstract

College students graduating in a recession have been shown to face large and persistent negative effects on their earnings, health, and other outcomes. This paper investigates whether students delay graduation to avoid these effects. Using data on the universe of students in higher education in Brazil and leveraging variation in labor market conditions across time, space, and chosen majors, the paper finds that students in public institutions delay graduation to avoid entering depressed labor markets. The delaying effect is larger for students with higher scores, in higher-earnings majors, and from more advantaged backgrounds. This has important implications for the distributional impact of recessions.

**JEL Codes:** I23,I24,J24,J21

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# 1 Introduction

College students face strong and persistent adverse effects when graduating in a recession. A recent survey by von Wachter (2020) finds that, on average, college students graduating in a recession earn 10% less, an effect that persists for ten years following graduation.<sup>1</sup> Altonji, Kahn and Speer (2016) and Arellano-Bover (2020a) attribute part of these effects to students graduating in a recession finding their first jobs in lower-paying occupations or with smaller firms. Forsythe (2020) documents that hiring rates fall faster for young workers during recessions. The adverse effects of graduating during a recession are not limited to labor market outcomes: cohorts graduating in recessions experience worse outcomes on health, family formation, and crime (von Wachter, 2020).

This begs the question of whether college students postpone graduation to avoid entering a depressed labor market. While there are direct and opportunity costs of delaying graduation, these costs could be outweighed, for some students, by avoiding the scarring effect of unemployment and finding a better match in the labor market later on. Universities facilitate networking opportunities and provide infrastructure to help job-seeking students, which can be more valuable with higher labor demand. Additionally, maintaining status as a student can be beneficial since this status can be associated with: subsidies (e.g., transportation fares, cultural activities), internship opportunities, and the possibility of increasing human capital by attending more courses.

Whether (and for whom) the benefits outweigh the costs is, ultimately, an empirical question. In this paper, I investigate if college students' graduation decisions are affected by the local labor market conditions. The answer to this question can add to our understanding of the drivers of the labor market participation of young individuals. By investigating

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<sup>1</sup>Arellano-Bover (2020b) reviews papers exploring the graduating-in-a recession effect and shows that there is documented evidence from Austria, Belgium, Britain, Canada, Finland, Japan, Korea, Norway, Spain, and the United States of America.

which students avail of opportunities to delay graduation, I highlight a new dimension of heterogeneity in the costs of recessions.

To answer these questions, I bring together a rich collection of data. For college students, I use both administrative data containing the universe of college students in Brazil and detailed transcripts data from one large university. I combine them with several sources of information on local labor markets, including a national matched employer-employee data. The empirical strategy uses a local major-weighted measure of new hires, exploring three sources of variation in employment conditions: across time, space, and chosen majors.

My primary data set consists of longitudinal data for the universe of students enrolled in any higher education program in Brazil, the Higher Education Census. Starting in 2009, annual microdata for every student enrolled in a technical or bachelors-equivalent program is available from admission until they graduate or drop out. For every student, I have demographic information, characteristics of the chosen major and institution, and, critically, the expected and actual graduation dates. Using a national matched employer-employee dataset, I construct a measure for the labor market conditions specific for each major and state, which I term the major-weighted hires (MWH). To construct it, I first obtain the distribution of occupations for each major. Then, I retrieve the number of hires for each occupation and state in the matched employer-employee data. The final measure is the average of the new job spells, weighted by the importance of each occupation for each major. Like common measures of the labor market conditions, such as *local* unemployment rates, MWH explores labor market variations across time (students expected to graduate at different years) and geography (students graduating in different states).<sup>2</sup> However, MWH provides unique detail by major; students from the same state with the same expected graduation date may have different labor market opportunities, depending on how the typical occupations for their majors are trending.

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<sup>2</sup>Since majors have different expected durations (from 3 to 6 years), even controlling for cohort, I can still explore residual variation in expected graduation time.

I first show that when students face a worse labor market, they are less likely to graduate on time. This effect is solely driven by students in public institutions — reducing the *weighted* hiring by 1% implies that students in public universities are 0.07pp less likely to graduate on time. In the 2014-2016 recession in Brazil, the weighted hiring fell by 30% on average, implying that the on-time graduation rate for public students was 2.1pp lower.<sup>3</sup> Given the baseline on-time graduation rate of 32.4% in public universities, this effect represents a 6.5% reduction in graduation at the expected time. In terms of the unemployment rate, this effect translates to the on-time graduation falling 0.4pp for an increase of 1pp in the unemployment rate.

Looking to the effects across all semesters, a recession increases the average graduation time by around 0.11 semesters. That is equivalent to 1 out of 18 students (5.5%) delaying graduation by one year. This effect is robust to different specifications and alternative employment measures, including the state unemployment rate, the most common measure in the literature.

In contrast, for students in private institutions, I find that recession has a near-zero effect on rates of delayed graduation. These contrasting results are not surprising given the institutional differences between public and private institutions. Public institutions are, on average, of better quality, tuition-free, and therefore highly selective. Students in public universities have better grades, are less likely to work while in college, and have better socioeconomic status than students in private institutes. Differences in course quality, the proportion of students working, and proxies for socioeconomic status can only account for part of the gap in the public-private estimates. Therefore, it is likely that public institutions being tuition-free plays a role in explaining these results. This makes the results from this paper important for several countries where the majority of the tertiary system is free or

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<sup>3</sup>The recession in 2014-2016 raised the unemployment rate by 5.5pp in Brazil. A recession that increases the unemployment rate by 4-6pp is the typical recession analyzed in the literature evaluating the effects of graduating in a recession.

with relatively low cost.

The effects of a recession on postponing graduation are more pronounced for students in higher-earnings majors and better socioeconomic status. We would expect this, given that students with more advantaged backgrounds have more family resources to rely on while postponing labor market entry. In particular, this suggests a channel through which the educational system might foster inequalities – more privileged students are better able to shield themselves from the adverse effects of labor market fluctuations by more freely choosing when to graduate.

I complement this analysis by gathering data from one large public university in the state of Bahia — The Federal University of Bahia (UFBA). UFBA is the state flagship university, admitting 4,200 students annually. This data has three main advantages. First, I have detailed information on course selection, credit accumulation, and entry scores that are not available in the primary dataset. Second, a subsample of the students responds to a socioeconomic questionnaire, from which I can extract better proxies for the socioeconomic status. Lastly, I can link this data to the matched employer-employee data and check whether students were working while in college.

I find that the effects for the UFBA sample are similar, albeit larger than what I obtained with the Higher Education Census. To investigate if students that delay graduation accumulate more credits, increasing their human capital, I instrument the graduation decision with the labor market measure (WMH). While the point estimate suggests that students induced to delay graduation take more credits, I do not reject the null hypothesis that the number of credits is the same as those not postponing.

With these data, I investigate several sources of heterogeneity in the recession effects, including whether students were formally working in the year before expected graduation. I find that the delaying effect comes entirely from students without jobs. Students that

had a formal job the year before graduation do not change their graduation decisions in response to the labor market conditions. This result supports the hypothesis that students are strategically delaying graduation for job-finding motives. I also show that delaying is higher for students with higher entry scores in the admission exams. Lastly, exploring heterogeneity across parental education, type of high school, and family income, I confirm the Higher Education Census results indicating that students from more advantaged backgrounds are more likely to postpone graduation when facing a recession.

Several papers document the negative effects for college students graduating in a recession (Genda et al., 2010, Kahn, 2010, Oreopoulos et al., 2012, Altonji et al., 2016, Schwandt and Von Wachter, 2019, Arellano-Bover, 2020a, Rothstein, 2021). This paper contributes to this literature by showing that some students react to the labor market conditions by delaying graduation. There is abundant evidence that the choice to enter college is responsive to labor market conditions (Betts and McFarland, 1995, Card and Lemieux, 2001, Petrongolo and San Segundo, 2002, Raaum and Røed, 2006, Clark, 2011, Hershbein, 2012, Barr and Turner, 2013, Sievertsen, 2016, Stuart, 2020). Here, I explore a different margin, showing how students in the final years of college still respond to the labor market conditions by adjusting the time of graduation and, therefore, when to fully join the labor market. So, even if some individuals do not change their educational attainment, they still respond to the environment by adjusting graduation timing.

The heterogeneous effects complement the findings and supplement our understanding of existing literature. Genda et al. (2010), Oreopoulos et al. (2012), Altonji et al. (2016), Schwandt and Von Wachter (2019) and Arellano-Bover (2020a) find stronger negative scarring effects for students in lower-paying majors and with lower socioeconomic status. This is consistent with my findings that there is a smaller delaying effect for students with less advantaged backgrounds. My results reinforce the inequality concerns about who bears the costs of recessions raised by these papers.

My paper relates to other papers that evaluate the relationship between labor market characteristics and late graduation. Chen and Yur-Austin (2016) uses survey data from students in one university in California and shows how more pessimistic students about the labor market are more likely to plan a late graduation. Bozick (2009) uses a survey of high schools in the United States from 2003-2004 and shows evidence that some college institutions can serve as a *warehouse* to accommodate students in times of a depressed labor market. Messer and Wolter (2010) uses a sample of Swiss graduates from 1981-2001 and shows that higher unemployment leads to a lower time-to-degree. Lastly, Aina and Casalone (2020) explores a sample of students graduating in 2002-2003 from 24 universities in Italy, showing that unemployment rates can be associated with late graduation and that this delay is costly for students. Relative to this work, my paper offers several contributions. First, with the Higher Education Census, I cover the universe of tertiary students in Brazil from more than 2,300 higher education institutes and 40,800 programs expected to graduate in 22 different semesters. This better coverage is not only beneficial to estimating the effect for a more representative sample but is essential to gauge the heterogeneity analysis. The different results depending on the type of university (public versus private), type of majors, characteristics of the program, and individual characteristics, including family background, are paramount to understanding the college-market transition and the effects of recessions. Second, my sample does not rely on students graduating in a given year, making it possible to control for cohort and still explore the effects of different labor market conditions — while the papers mentioned above do not separate cohort effects from labor market effects. Lastly, this paper also highly benefits from the matched employer-employee data, which allows me to compute labor market measures that vary not only across time and space, but also across majors, yielding finer variation of the main labor market measure, which is arguably closer to the relevant consideration for college students from a specific major than just the general unemployment rate for the entire population. Also, the inference procedure does not impose strong assumptions, such as the non-correlation within geography or major over time.

The large difference in the effect of recession on delaying graduation between public and private institutions demonstrates the key role of the institutional setting. With lower direct costs of delaying (i.e., tuition) and higher expected future gains (higher-paying majors), we should expect larger effects on postponement. These results are in line with Garibaldi et al. (2012) who shows that higher tuition causes lower late graduation in the Italian context. It is also consistent with the cross-country evidence from Brunello and Winter-Ebmer (2003) showing that students facing higher tuition costs have shorter college duration. This can partially explain why Oreopoulos et al. (2012) and Schwandt and Von Wachter (2019) do not find large effects in the timing of graduation in their settings.

Moreover, my results provide an explanation for Kahn (2010) and Arellano-Bover (2020b)'s findings of larger effects when instrumenting the labor market conditions by the unemployment rate of expected graduation than in the OLS specifications. The compliers in their instrumental variables approach are precisely those not delaying graduation. I show that these students who do not delay graduation are more likely to be in lower-earnings majors and less advantaged backgrounds.

This paper proceeds as follows. I present the institutional setting of higher education in Brazil (Section 2); discuss the benefits and costs of delaying graduation (Section 3); present the data sets (Section 4); discuss the empirical strategy and the construction of the labor market measure (Section 5); present and discuss the empirical findings (Section 6); and offer concluding remarks (Section 7).

## **2 Institutional Setting**

### **2.1 Higher Education System in Brazil**

As in many countries, admission to higher education in Brazil is institute and major specific, commonly based solely on scores from admission exams. When students are admit-



ted to a higher education institute, they are associated with a given major and a schedule depending on the period of classes: morning, afternoon, morning and afternoon, or evening. In this article, I will always refer to the major-institution-schedule as a *program*.

In Brazil, higher education institutes can be universities, colleges, or college-centers (*Centros Universitários*), depending on the range of degrees and majors offered. I do not distinguish between them, and I use the terms institutes or universities interchangeably. However, I make a key distinction between public and private institutes. Public institutions can be administered by the federal, state, or municipal governments and are typically large research institutes. They do not charge any tuition and tend to have high-quality programs. Private institutes can be for-profit or nonprofit organizations, charge tuition, and are, on average, of lower quality than their public counterparts. Tuition in private institutes varies by major and institutions. In 2017, the average monthly tuition for a business major was 262 USD (ranging from \$57 to \$1,502); while the average monthly tuition for a medicine major was 2,010 USD (\$1,095 to \$3,879).<sup>45</sup> In 2017, the average monthly per capita household income in the country was 389 USD.<sup>6</sup>

Since the public institutions are tuition-free and of superior quality, it is not surprising that they are highly selective. During my sample period, admission at public institutes had, on average, 12.1 candidates per seat, compared to only 1.6 in private institutions.<sup>7</sup> Public universities account for roughly one-quarter of all college students.

It is worth highlighting two additional aspects of the education system in Brazil. First,

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<sup>4</sup>To the best of my knowledge, there is no systematic collection of tuition data in the country. These numbers are from a survey conducted by a student guide publication (*Guia do Estudante*). The numbers from 2017 are available at this link: <https://web.archive.org/web/20211118174614/https://guiadoestudante.abril.com.br/universidades/quanto-custa-fazer-uma-faculdade/>

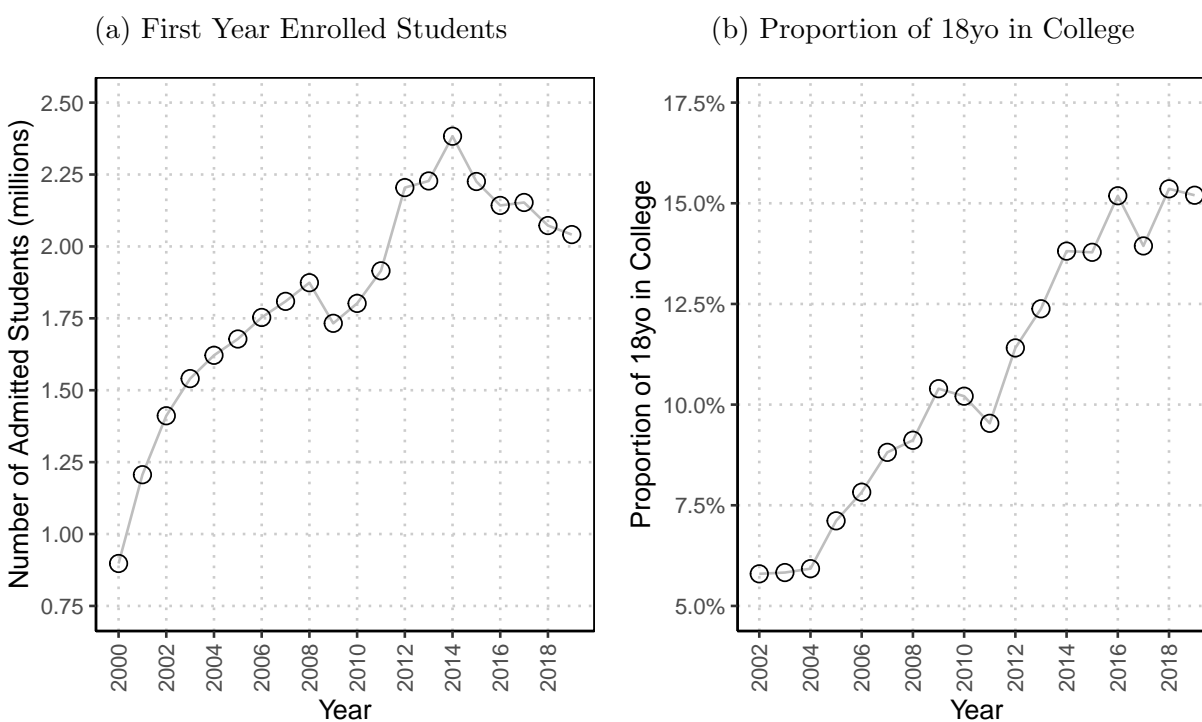
<sup>5</sup>Using a conversion of 1USD to 3.30 BRL in June of 2017.

<sup>6</sup>1,285 BRL, using the household survey PNADC (*Pesquisa Nacional por Amostra de Domícios Contínua*).

<sup>7</sup>These numbers were drawn from the summary statistics for higher education produced by the INEP agency, linked to the Ministry of Education. For each year, I compute the number of applicants divided by the number of seats. The 12.1 and 1.6 are the average of this ratio for public and private institutions from 2009 to 2019.

graduate programs are not a popular choice after obtaining bachelor’s degrees. Only 4.6% and 1.4% of those with bachelor’s degrees have M.A. and Ph.D. degrees.<sup>8</sup> Second, while public universities are of better quality and highly selective in higher education, the opposite occurs in primary and secondary education. Public primary and high schools are of inferior quality compared to their private counterparts, serving students from less advantaged backgrounds.<sup>9</sup> In the heterogeneity analysis, I will use the type of high school (public or private) as one of the proxies for socioeconomic status.

Figure 1: Time trends of college enrollment in Brazil



Notes: The panel on the left shows the number of admitted students in higher education across time. The panel on the right shows the proportion of 18 years-old individuals enrolled in any higher education program. The number of first-year enrolled students comes from the summary statistics produced by the INEP agency linked to the Ministry of Education. The proportion of 18 years old enrolled in higher education was computed using the household surveys (PNAD for the years 2002-2009 and 2011, Demographic Census for 2010, and PNADC for 2012-2019).

<sup>8</sup>Using data from the Education at Glance 2019, produced by the OECD.

<sup>9</sup>In the Appendix Figure A.1 I show the distribution of standardized scores for students in public and private schools for 5th, 9th, and 12th-graders, as well as for college students. Approximately 85% of primary and secondary students are in public schools, with worse average scores than students in private schools. In Higher Education, we see the opposite. Less than 25% of students are in public universities, and they exhibit higher average scores.

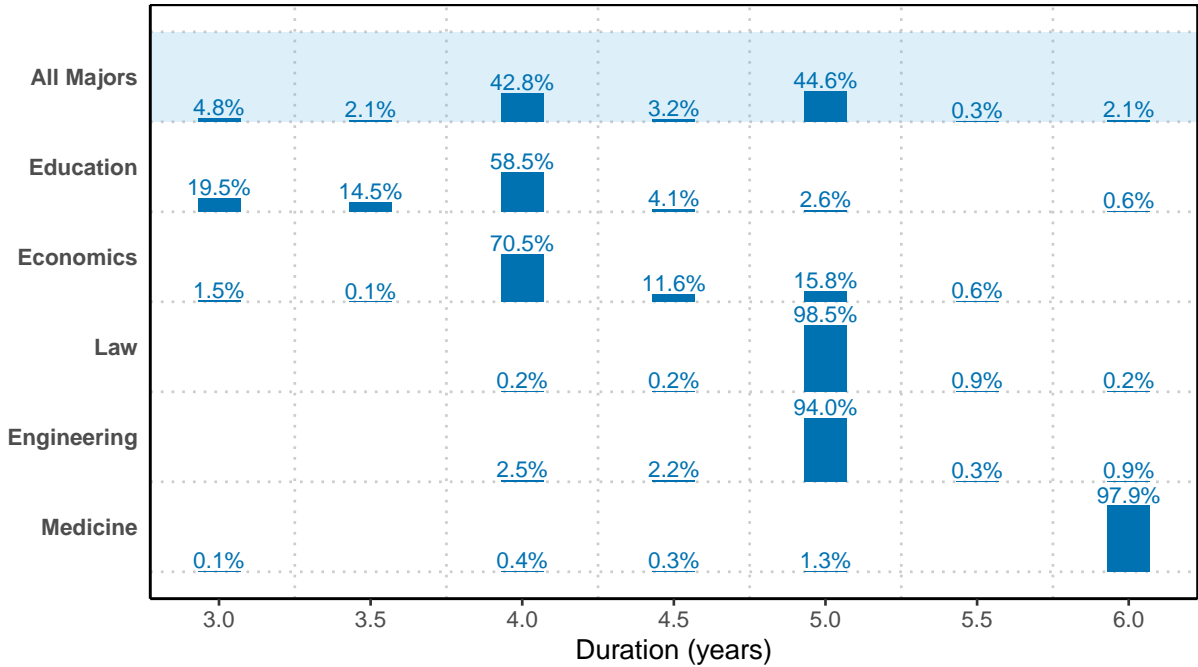
Figure 1 shows time trends on college enrollment in Brazil in the 21<sup>st</sup> century. In panel (a), we can see that the number of students enrolled in the first year rose from 0.9 million to 2.4 million in 2014 and later decreased to 2.0 million in 2019. The growth is due mainly to public policy at the federal level that created several new public higher education institutions and expanded programs providing scholarships and student loans for private institutions. These programs were severely affected by the 2014-2016 crisis and thus drastically reduced. In the second panel, we can see that this expansion was not merely due to population growth. The proportion of 18 years old students enrolled in higher education jumped from 5.8% to more than 15%.

## 2.2 Major duration and on-time graduation

Programs' duration is given by the time students would take to graduate following the recommended course schedule. I will always refer to this time as the expected duration. Each program has a different duration, typically between 3 to 6 years. The first row of figure 2 shows the distribution of students according to their program duration. We can see that the most typical programs' lengths are 4 and 5 years, accounting for, respectively, 42.8% and 44.6% of students. I show the same distribution for five different majors in the subsequent five rows. Almost 60% of students majoring in Education are in programs with an expected duration of 4 years. An Economics degree typically takes 4 years; a Law and Engineering degree takes 5; and a Medicine degree takes 6.

While variation in program duration can be primarily attributed to majors, there is still some variation within majors. In Educations and Economics, 40.5% and 30.5% of students, respectively, are enrolled in programs with different durations than the mode. There can even be variation in the length of a program within a major at the same institution. For instance, the major of Economics at the University of Sao Paulo has an expected duration of 4 years if the student is enrolled in the morning schedule but 5 years if the student is

Figure 2: Proportion of students by program duration



Notes: In each row, the figure shows the proportion of students enrolled in programs with different duration, from 3 to 6 years. In the first row is the distribution for all students enrolled in higher education. In the next five rows, I present the distribution for students majoring in Education, Economics, Law, Engineering, and Medicine. The numbers were calculated using the Higher Education Census from 2009 to 2019.

enrolled in the evening schedule. The number of credits and the courses are exactly the same for the two schedules.<sup>10</sup>

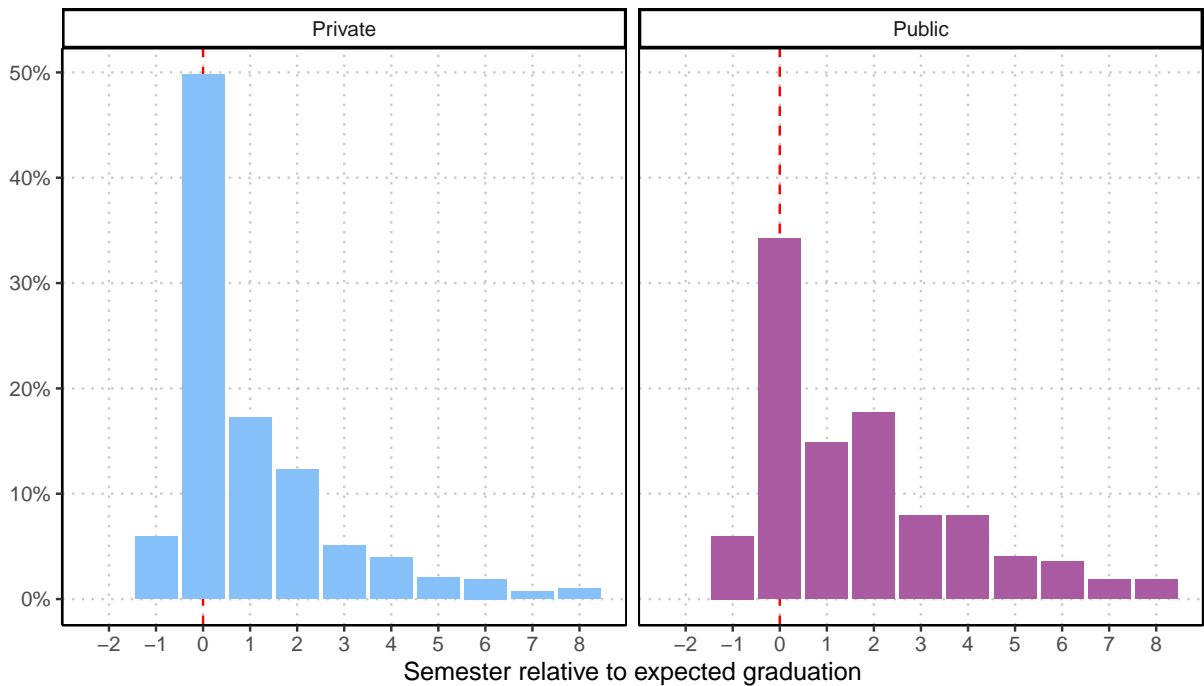
While the numbers above refer to the expected duration of each program, students can take much longer to graduate. Figure 3 shows the distribution of students graduating in each semester relative to expected graduation.<sup>11</sup> We can see that 50% of students in private institutions graduate at the expected time, while only 34% do the same in public institutions. While on-time graduation is the most common time to graduate for all institutions, more than half of students do not graduate in the expected semester. These numbers are similar

<sup>10</sup>Source for the morning schedule: <https://web.archive.org/web/20211207164935/https://www.fea.usp.br/economia/graduacao/estrutura-curricular/diurno>. Source for the evening schedule: <https://web.archive.org/web/20211207165432/http://www.fea.usp.br/economia/graduacao/estrutura-curricular/noturno>

<sup>11</sup>I consider all students that graduate between -1 and 8 semesters off from their expected graduation, which account for almost the totality of students graduating.

to those found in several European countries as reported by Brunello and Winter-Ebmer (2003), Garibaldi et al. (2012), Aina et al. (2018), Aina and Casalone (2020).

Figure 3: Distribution of time of graduation relative to expected graduation



Notes: The figure presents the proportion of students that graduate in each semester relative to the semester of expected graduation. The panel on the left shows the distribution for students in private institutions, while the panel on the right for students in public institutions. I restrict the figure to those students graduating between -1 and 8 semesters relative to the correct time and that were enrolled in the first semester of their expected year of graduation.

### 3 Graduation and the Labor Market Conditions

Existing literature documents the negative and persistent effects of graduating in a recession. More recent work has shown that initial placement is a critical driver of these negative results (Altonji et al., 2016, Arellano-Bover, 2020b). Therefore, students near graduation could consider extending their college experience by delaying graduation and avoiding entering a depressed labor market. There are both costs and benefits associated with this decision.

Postponing graduation can be costly, as students who postpone forgo the labor earn-

ings they would receive upon finding a job after graduating. There are additionally direct monetary costs when staying enrolled, namely the tuition and other costs when in college (housing, materials, and others). It is also possible that postponing graduation is a bad signal for firms.

In terms of benefits, students could avoid the scarring effect of unemployment since it is difficult to find jobs when graduating in a recession.<sup>12</sup> An extra semester of college studies may look better to future employees, especially when unemployment is the counterfactual. Additionally, the university’s infrastructure and network may be a more valuable resource as more active is the labor market. Students can also take the extra time to complete more credits and increase their human capital. Moreover, students are only eligible for internships when they are in school. Lastly, students have subsidies for transportation fares, food (in some public institutions), and cultural activities.

Table 1: Summary of costs and benefits associated with delaying graduation

<b>Costs</b>	
(C1)	Forgone earnings while in college
(C2)	Direct costs of attending college (tuition and others)
(C3)	Worse signal for firms in the job-searching
<b>Benefits</b>	
(B1)	Avoid the scarring effects of unemployment
(B2)	Universities job-finding resources more valuable with higher demand
(B3)	Complete additional coursework
(B4)	Remaining eligibility for internships
(B5)	Access to students’ subsidies (e.g. transportation, cultural activities)

Table 1 summarizes the discussed costs and benefits. Given that existing literature concludes that early graduates during a recession have low earnings, foregone earnings while remaining in college (C1) may be limited, and the potential benefits of a better match after postponing graduation, given by avoiding the scarring effects and the use of the university

<sup>12</sup>The scarring effect can also include the psychological effects or the social pressure of being out of the university and unemployed.

resources to find jobs (B1-B2) could be substantial. Garibaldi et al. (2012) shows how direct costs (C2) are highly relevant: lower tuition increases students' time to complete the degree. For the cost of a worse signal (C3), it is important to know how firms view students' decision to postpone. While I cannot speak to the thinking of firms, it seems that it would be difficult for firms to know precisely the expected graduation time. Students in the same cohort and the same major (and in some cases, even in the same major and institution) can have different expected graduation times. Moreover, more than 50% of students do not conclude their programs in the semester of expected graduation, so delaying graduation is likely not stigmatized.

Additionally, Malacrino and Saggio (2017) show that the market values the number of credits taken and not only whether the degree was obtained or not, implying that the opportunity of completing additional courses (B3) is not negligible. Nunley et al. (2016) also shows that internships are valuable in the job search, attributing option value to staying in college (B4).

Whether the benefits outweigh the costs is an empirical question. We can undoubtedly expect highly heterogeneous effects since it is likely that those benefits and costs vary a lot from student to student and with their family's resources. Also, we may expect some students to be in corner solutions, where small variations in each component would not change the time of graduation.

The institutional setting presented in the last section hints that we should expect different results for students in public and private institutes. First, public schools do not charge tuition, making their students' direct costs (C2) orders of magnitude lower. As discussed in the last section, tuition costs in private universities can be high (in some programs, tuition is higher than the average income per capita). On average, public universities are larger, higher quality, and more prestigious, suggesting that the value of the university resources (B2), additional courses (B3), and the opportunity of the additional internships (B4) are

larger for them. Given that students in public institutions have better scores and higher earnings potential, the tradeoff between avoiding the scarring (B1) and forgone earnings (C1) may be pronounced for them. Lastly, students in public universities have access to many more subsidies than their private counterparts, making (B5) arguably larger for them. Therefore, I hypothesize that the effects of delaying graduation are larger for students in public universities.

While my empirical strategy does not isolate the effect of each individual cost and benefit, it will shed light on the relative importance of some factors. One exception is on human capital. With the data from UFBA, I investigate directly whether accumulating more credits is an important channel.

## 4 Data

The primary data set is the Higher Education Census, containing annual microdata for every student enrolled in a higher education institute in Brazil from 2009 to 2019.<sup>13</sup> For each student, the set includes information on the admission year, major, institute, and status (enrolled, on leave, or graduated). There is also basic demographic information, including date and place of birth, gender, and race. The level of observation is at the enrollment level, that is, a student-institute-major combination. From 2009 to 2017, it is possible to track students over time; however, starting in 2018, the individual identifiers are year-specific. Using a matching algorithm combining demographics and major-institution information, I link students over time, generating a panel that spans 2009 to 2019.<sup>14</sup> In the Appendix table A.4 I show that the results are robust to only considering the data until 2017, where the unique identifiers are presented. I then restrict the data set, keeping students from in-person

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<sup>13</sup>The Higher Education Census (*Censo da Educação Superior*) is collected by the INEP agency (*Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira*), linked to the Ministry of Education.

<sup>14</sup>The matching procedure matches students by gender, date of birth, place of birth, major, university, and admission date, which is sufficient to uniquely identify individuals 95% of the time. This procedure is detailed in Appendix B.



bachelor-equivalent programs who are between 17 and 22 years of age when admitted and who have expected graduation dates before 2019. The resulting sample has 7.8 million unique individuals enrolled in 40,849 different programs, which are a combination of 74 majors, 2,342 higher education institutes, and 4 different schedules (morning, afternoon, morning-afternoon, and evening). Appendix B contains more details about the data manipulation and the sample selection.

Most of the analysis is based on a subsample of students enrolled in their expected graduation year. This is a sample of interest because I am testing whether students that could graduate decide to postpone graduation when facing worse labor market conditions. My analysis does not speak to the dynamics of the first years in college. This sampling definition is similar to the one by Oreopoulos et al. (2012). This restriction also maximizes the number of cohorts in the analysis. As the data only starts in 2009, the inclusion of all students enrolled in their first year would only allow me to track students entering in 2009 (with expected graduation dates between 2011 and 2014); whereas by restricting to the students enrolled in their final year, I can use all the cohorts with expected graduation dates between 2009 and 2019.

The Higher Education Census is valuable because of its breadth, covering the entire population of students in Brazil. However, it lacks more detailed information, such as credit accumulation, admission scores, and socioeconomic information at the individual level. To complement the analysis, I obtain from the *Universidade Federal da Bahia* (UFBA), a large public university in the state of Bahia in Brazil, transcripts data from all students admitted between 2003 and 2017. The data contains the admission year, major, and courses enrolled in each semester for every student, including their course outcome (pass, fail, or dropped out) and their scores. I can also access the questionnaire that some students submit during the admissions process, which asks about students' demographics and socioeconomic standing. UFBA is the largest university in the state of Bahia, admitting about 4,200 students per

year. With these data, I construct a panel of all students admitted between 2003 and 2015 and expected graduation in 2005-2017. I also apply the same restrictions I applied to the Higher Education Census sample, looking only at students in their last year, as detailed in Appendix B.

I complement the information on student majors and institutions with two additional sources of data. First, since 2004, the INEP agency has assessed the quality of higher education courses with an exam for first-year students and graduates called ENADE.<sup>15</sup> I use the final scores of this exam as a measure of program quality. I also utilize data from a personal questionnaire that students answer on the ENADE exam to extrapolate the percentage of students who work while in college, the percentage of students who completed high school in public schools, and parental education levels. Second, with unique individual identifiers, I can also link students from UFBA to the Brazilian matched employer-employee dataset (RAIS), allowing me to identify whether specific students are working formally while in college.<sup>1617</sup>

I use several additional datasets to measure labor market conditions. From the Demographic Censuses in 2000 and 2010, I obtain the distribution of occupations for individuals that graduated from each major. The matched employer-employee dataset allows me to compute the stock of employees and the number of new hires in each occupation, state, and time. Additionally, I use the household surveys (PNAD and PNADC) from 2002 to 2019 to estimate population counts and unemployment rates. Section 5.1 details how these pieces of information are used to construct the labor market measure, and there are further details in Appendix B.

Table 2 shows the descriptive statistics of my two main datasets. I divide the students

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<sup>15</sup>ENADE stands for National Students' Performance Assessment (*Exame Nacional de Desempenho de Estudantes*).

<sup>16</sup>I match students by their social security number (*"Cadastro de Pessoa Física"* CPF).

<sup>17</sup>RAIS (*Relação Anual de Informações Sociais*) is an annual matched employer-employee dataset, collected by the Ministry of Labor and the Ministry of Economy.

Table 2: Descriptive statistics

	Mean			Number of Observations		
	Private	Public	UFBA	Private	Public	UFBA
On-time graduation	0.457	0.324	0.216	3,129,095	1,540,563	42,154
<u>Demographics</u>						
Age at admission	19.310	19.246	-	3,343,106	1,622,900	-
Female	0.609	0.561	0.551	3,343,106	1,622,900	29,550
Black or Native	0.335	0.404	0.754	1,992,907	1,047,273	25,465
<u>Program-level variables</u>						
Top-10% programs (ENADE)	0.051	0.354	-	3,106,390	1,314,787	-
Top-10% programs (CPC)	0.062	0.166	-	3,104,399	1,313,623	-
≥50% of mothers with College+	0.147	0.254	-	3,014,310	1,254,876	-
≥50% from public high-schools	0.614	0.436	-	3,014,310	1,254,876	-
≥50% working full-time	0.310	0.080	-	3,014,310	1,254,876	-
<u>Individual-level variables</u>						
Working full-time in Junior Year	-	-	0.208	-	-	42,154

Notes: Descriptive statistics for the sample of students in the Higher Education Census by type of institution (private or public) and for the sample of students in UFBA. The first three columns present the sample mean and the last three columns the number of observations with non-missing information for each variable. Junior year is the year before expected graduation. Top-10% programs classified using the ENADE score.

from the Higher Education Census by institution type (public or private). In line with the discussion in section 2.1, we can see significant differences across the two types of institutions. Students in private universities are more likely to graduate on time (45.7% x 32.4%), more likely to be women (60.9% x 56.1%), and less likely to be Black or Native (33.5% x 40.4%). I use two measures of course quality, one based on the ENADE exam, computed as the average of students graduating from a given program. The other (CPC) is produced by the Ministry of Education, combining data from the ENADE exam and information on the program infrastructure e faculty composition. While 35.4% of students in public institutions are enrolled in programs classified in the top-10% of ENADE score, only 5.1% of students in private schools are in these top programs. We have a similar picture for the CPC measure, but with a lower fraction of students in public universities enrolled in the top 10% programs. In terms of socioeconomic status, only 14.7% (24.4%) of students in private (public) schools

are enrolled in programs in which at least 50% of students have mothers with college degree or more, and 61.4% are enrolled in programs where more than half of students graduated in public high schools. Strikingly, 31% of students in private universities are in programs where more than half of students work full-time while in college, versus just 8% in public institutions. Students at UFBA have lower on-time graduation rates (21.6%) and a much higher proportion of Black students (75.4%) — this is in line with the overall demographics of the state, which is the state with the highest proportion of Black people in the country. For the UFBA sample, 1 in 5 students works full-time in the year before their expected graduation.

## 5 Empirical Strategy

The empirical strategy explores variation in employment conditions over time, geography, and chosen majors. Student  $i$  was admitted in college in the year  $t_0(i)$ , in the major  $m(i)$ , and, given the length of their major, they are expected to graduate in the year  $t_1(i)$ . They are studying in state  $s(i)$  in program  $p(i)$ , a combination of major-institution-schedule. My main specification regresses the dummy outcome variable for on-time graduation  $Y_i$  on an employment measure that varies across time-space-major ( $H_{t_1(i),s(i),m(i)}$ ).

$$Y_i = \beta H_{t_1(i),s(i),m(i)} + \eta_{t_0(i),m(i)} + \nu_{p(i)} + \gamma X_i + \varepsilon_i \quad (1)$$

I control flexibly for the time of entry by adding admission-year fixed-effects for each major ( $\eta_{t_0(i),m(i)}$ ). As discussed in section 2.1, tertiary enrollment in Brazil rose steadily in the first 15 years of the 20th century. Therefore, I am careful in my analysis not to capture the effects arising from this unrelated trend. The introduction of the  $\eta_{t_0(i),m(i)}$  term still allows for some variation in the time of graduation because programs have different duration. I also add program fixed effects ( $\nu_{p(i)}$ ) that absorb fixed unobserved factors that

vary by major-institution-schedule of study, and individual level controls ( $X_i$ ) that include demographic controls for gender, race, and age at admission. In section 2.1, I discussed the differences between public and private institutes in Brazil and why we expect different results for them. Therefore, I analyze public and private institutions separately.

I am interested in analyzing  $\beta$ , which will capture the effects of the current labor market conditions on on-time graduation for students in public and private universities. I clustered the standard errors at both the major and the state level (*two-way cluster*), allowing for arbitrary correlation within states as well as for students in the same major.<sup>18</sup>

The coefficient  $\beta$  captures the causal effect of the labor market conditions on graduation decision provided that, conditional on the included covariates, there are no unobserved components correlated with the labor market measure and the graduation decision. While this assumption is not testable, I show in the Appendix table A.5 that, conditioning on the set of fixed effects (excluding the demographic cells fixed effects), individual characteristics of the students (gender, race, and age of entry) are not correlated with my labor market measure. One potential threat is, for instance, if labor market shocks are correlated over time, and negative shocks affect their performance in the first years in college. If that is the case, then what I interpret as a delaying effect is, instead, just students being unable to graduate because they did not accumulate enough credits to graduate on time. Other concerns are the selectivity of state and major of graduation, which could be correlated with future labor market shocks. I discuss how my results are robust to these concerns in Section 6.3.

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<sup>18</sup>When showing the results for the UFBA sample, I clustered the standard errors at the major level because for these exercises, all students graduate from the same state.

## 5.1 Employment Measure

The exercise requires a measure for the labor market conditions faced by student  $i$ , majoring in  $m(i)$ , who is expected to graduate at  $t_1(i)$ , in state  $s(i)$ . Most of the literature covered by von Wachter (2020) uses the unemployment rate at some sub-national level (state, provinces). I leverage the matched employer-employee dataset to have finer variation at the major level, similar in spirit to the major-specific unemployment rates by Altonji et al. (2016). This allows me to explore variations across time, geography, and also major.

I obtain the distribution of occupations across majors for all individuals with a college degree from the Demographic Census in 2000 and 2010. I construct the vector  $w_m = (w_m^1, w_m^2, \dots, w_m^{N_{occ}})$  for each major  $m$ , where each component is the proportion of individuals from major  $m$  that are employed in each of the  $N_{occ}$  occupations. For example, if half of those graduating in economics work in occupation 1, then  $w_{\text{economics}}^1 = 0.5$ . These weights vary greatly across majors and are fairly constant over time.<sup>19</sup>

Using the matched employer-employee data, I compute for each state and occupation the number of new hires in a given semester, defined as  $h_{ost}$ .<sup>20</sup> Occupations are defined in the 4-digit level, using a cross-walk between the codes in the Demographic Censuses and RAIS. I use hires because it is closely related to the chances a student graduating would be able to find a job in a given period. Importantly, in order to avoid mechanical effects, I compute new hires only for individuals aged 27 or above. Given my age of entry restrictions (17-22), less than 0.01% of my sample is 27 at expected graduation, and more than 96% are younger than 27 even two years after expected graduation.

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<sup>19</sup>I compute the correlation between  $w_m$  and  $w_{m'}$  for all pairs of majors — the median value is 0.15, evidencing that they vary across majors. I also show that weights are constant over time by computing the weights separately for the years 2000 and 2010 and computing the correlation of  $w_{m,2000}$  with  $w_{m,2010}$  for all majors — the median correlation is 0.87. Figure A.2 shows the full distribution of these two metrics.

<sup>20</sup>To avoid seasonal effects, I aggregate this measure annually. For the 1st semester of year  $t$ , I aggregate hiring from the first semester of  $t$  with the second semester of  $t - 1$ . For the second semester of year  $t$ , I use hires from both semesters of  $t$ .

With  $w_m$  and  $h_{ost}$ , I construct the Major-Weighted Hiring measure as a weighted sum of the new hires for each occupation and state:

$$MWH_{tsm} = \sum_o w_m^o h_{ost} \quad (2)$$

Therefore, students expected to graduate in majors whose typical occupations are hiring more will face a larger  $MWH$  than students graduating from majors whose typical occupations have a hiring freeze. I will use  $\log(MWH_{tsm})$  as the labor market measure in equation 1 to capture *percentual* variations of the labor market conditions. Therefore  $\beta$  can be directly read as the effect of a 100% variation on the (weighted) hires.

In order to compute reliable estimates for  $MWH_{tsm}$ , I apply some sample restrictions to remove occupations that are affected by changes in the occupation codes structure introduced in 2008-2012. I also remove majors where I observe a small number of individuals in the Demographic Census or where most graduates work in occupations not considered in the study. These restrictions are detailed in the Appendix B. Reassuringly, I conduct a sensitivity analysis in the Appendix A.3 showing that the results do not rely on the specific thresholds considered.

Figure 4 shows that the proposed measure closely tracks changes in the unemployment rate and variations in the GDP. This figure uses the variation in the annual hiring counts for the entire country. Brazil experienced a major recession in 2014-2016, during which the GDP fell by 4% for two consecutive years, increasing the unemployment rate by 5.5 percentage points from 6.5% to 12%. Figure 5 plots the variation of the hiring measure for all major-state pairs across time (each gray dot), which is the variation that my analysis specifically explores. Brazil has 26 states and 1 federal district, and I have information for 64 majors, yielding a total of 1,728 major-state pairs. Besides tracking the variations in the GDP and employment closely,  $MWH$  has two main advantages over these measures:

it has a finer variation at the major level and is likely close to the real consideration set of students. A student graduating in engineering responds more to how occupations that typically hire engineers, like industry, construction, and the financial sector are trending than in health-related occupations.

Figure 4: Economic activity measures



Notes: The first panel shows the annual variation of the Brazilian GDP. The second panel shows the national overall unemployment rate across time. The third panel shows the annual variation of the hiring measure.

For the UFBA sample, I compute the major-weighted hiring with a similar procedure. The only distinction is that I obtain the major weights directly by linking the data from UFBA graduates and the matched employer-employee data set. The analysis of reliability and uniqueness are also presented in Figure A.3. Note that I am only able to explore variation across time and major for this sample since all students graduate in the same state.



Figure 5: MWH for major-state pairs across time



Notes: The blue bars are the annual national variation for the hiring variable. Each gray dot shows the annual variation (first differences) of the major-weighted hiring measure for one major-state pair. I spread the dots on the x-axis to improve the visualization — all dots in the same “block” are from the same year.

## 6 Results

For ease of exposition and to better align with existing literature, I multiply the coefficient of interest ( $\beta$ , from equation 1) by minus one. Therefore all the coefficients can be interpreted as a 100% decrease in the major-weighted hiring measure.

### 6.1 Main Results

Table 3 present the baseline results. The first column shows that by decreasing the hiring measure by 1%, on-time graduation is reduced by 0.014 percentage points. In the second column, I estimate this effect separately for public and private universities. We can see that a 1% reduction in hiring implies that students in public universities are 0.08pp less likely to graduate. For students in private institutions, we see a small positive estimate. I

reject that the two effects are the same with a p-value of 0.032. The specification in the second column includes fixed effects for each major-state and a quadratic trend on admission year. In the third column, I add a richer set of program fixed effects defined at the major-institution-schedule level. In the fourth column, I include demographic fixed effects defined by gender, race, and age at admission.

Table 3: Main results

<i>Outcome:</i>	<i>On-time graduation</i>					
	(1)	(2)	(3)	(4)	(5)	(6)
Hiring	-0.014 (0.024) [0.577]					
Hiring x Public		-0.081 (0.031) [0.015]	-0.072 (0.031) [0.027]	-0.071 (0.030) [0.027]	-0.076 (0.033) [0.028]	-0.070 (0.031) [0.032]
Hiring x Private		0.004 (0.033) [0.898]	0.014 (0.027) [0.608]	0.019 (0.028) [0.505]	-0.023 (0.037) [0.540]	-0.003 (0.040) [0.934]
N Obs	4,058,758	4,058,758	4,058,758	4,058,758	4,058,758	4,058,758
p-value ( $\beta_{\text{public}} = \beta_{\text{private}}$ )	-	{0.032}	{0.012}	{0.015}	{0.132}	{0.084}
Major-State FE	✓	✓	-	-	-	-
Program FE	-	-	✓	✓	✓	✓
Demographics	-	-	✓	✓	✓	✓
Time Trend	Quadratic	Quadratic	Quadratic	Quadratic	Admission Time FE	Major-Admission Time FE

Notes: The table presents the estimation of  $\beta$  from equation 3. I multiply the coefficient by minus one, therefore, we can see the coefficients as a decrease of 100% of the weighted hiring measure. The recession between 2014-2016 reduced the weighted hiring measure by 30%. The first column presents the overall results. In columns 2-6, I interact all variables with an indicator of whether the students belong to a private or public institution. Columns 2-6 differ in the set of control variables included in each specification. Standard errors are clustered at both the major and state levels (*two-way clustering*). The p-value of the test whether the effect for public and private institutions are the same is provided for each specification. FE stands for fixed effects.

Section 2.1 showed how enrollment in college education in Brazil rose in the first 15 years of the 2000s. I want to be careful not to capture effects that can stem from the rise in enrollment. The first four columns from Table 3 include a quadratic trend on admission year, which act as a parsimonious control for any time-varying trend in tertiary education that may relate to the time of graduation. In the fifth column, I replace the quadratic trend with

a fully flexible admission time fixed effects, which does not impose any parametric restriction on the time trends. We can see that the results continue to be really close. In the sixth column, I allow for the admission time fixed effects to be major-specific. It can therefore account for any major-specific trends.

I will use the specification in the last column as the benchmark since it flexibly controls for time trends, allowing for major-specific trends. Reducing hiring by 1% implies a reduction of on-time graduation by 0.07pp for students in public universities. In the 2014-2016 recession, the average reduction on the hiring measure was 30%, implying a reduction of 2.1pp on on-time graduation. Considering the average on-time graduation rate in public universities of 32.4%, the effect translates to a 6.5% reduction in the on-time graduation rate.

We can see that across all specifications in Table 3 the estimates for students in public universities are robust, ranging from 0.070-0.081, while the estimates for students in private institutions are small, not statistically significant, flipping signs. To decide the graduation time, students in private universities are likely in corner solutions when comparing the costs and benefits discussed in section 3.

Public and private universities have several different characteristics: public universities are, on average, more selective, with better quality courses, with fewer students working while in college, when compared to their private counterparts. Importantly, public universities are tuition-free. In the Appendix A.1, I reweight the observations from private institutions to have the same distribution of the public universities along the following dimensions: majors offered, demographics of students, the proportion of students from public high schools, and quality. In none of the reweighting exercises, the public and private estimates are close. Reweighting for quality produces the estimates where the public-private gap is the smallest. Nevertheless, the point estimate for private institutions is only one-quarter of the estimate for public universities. While we do not have information on tuition, I speculate that the

fact that public universities do not charge tuition may be an important factor explaining these results. While students in private universities would need to pay tuition for the extra semesters of postponement, this direct cost is zero for students in public universities. This explanation is aligned with the findings of Garibaldi et al. (2012), who finds that increasing tuition reduces late graduation in the context of Italy. The result also is consistent with the cross-country evidence from Brunello and Winter-Ebmer (2003), which shows a shorter college duration for students facing higher tuition costs.

The previous results assessed whether on-time graduation responds to the labor market conditions at the time of graduation. Fewer students in public universities graduate on time when facing a more depressed labor market. However, we still do not know whether they postponed graduation or did not graduate at all. Figure 6 plots the effects of the baseline regression estimated separately for each semester relative to expected graduation for students in the public institutions. The outcome  $Y_i^\tau$  is now equal to 1 if student  $i$  graduated up to semester  $\tau$ , that is, the *cumulative* graduation up to  $\tau$  semesters after expected graduation. The estimate at (relative) semester 0 is the one presented in Table 3.

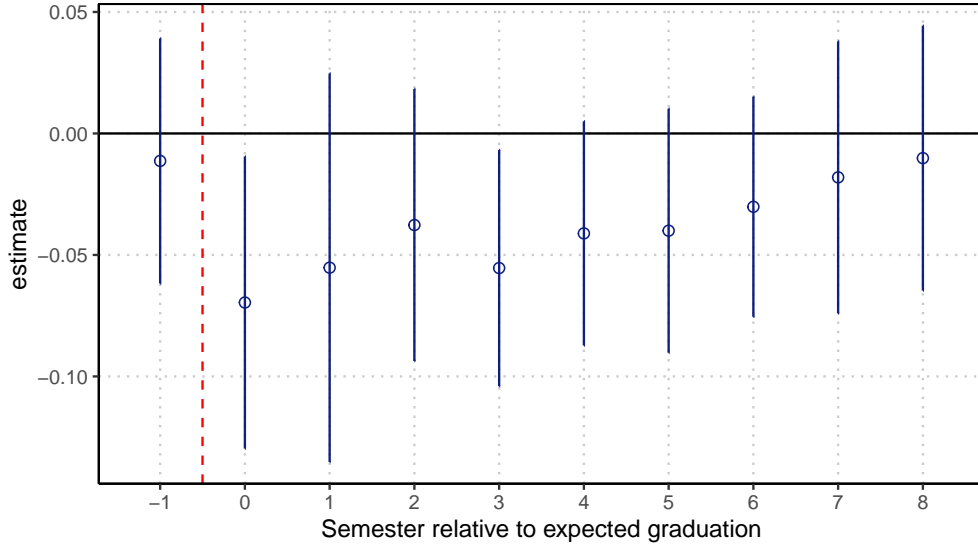
One semester before expected graduation ( $\tau = -1$  in the graph, on the x-axis), the point estimate is close to zero, dropping to -0.070 in the semester of expected graduation. After one year, the effect is around -0.037 and quickly becomes indistinguishable from zero. The fact that it does not have a significant effect four years after expected graduation shows that the labor market conditions can affect graduation timing but not whether students ultimately graduate. It is worth emphasizing that I am restricting to students who were enrolled in their expected year of graduation.<sup>21</sup>

Using the estimated effects displayed in Figure 6, I can compute what is the average delay response to changes in the hiring rates. My estimates imply that a 1% decrease in the

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<sup>21</sup>Note that for all regressions,  $MWH$  is fixed at the hiring rate observed at the expected graduation semester.

Figure 6: Effects on *cumulative* graduation by semester relative to expected graduation



Notes: The figure plots the estimation of  $\beta$  from equation 3 for students in public universities. I multiply the coefficient by minus one, therefore, we can see the coefficients as a decrease of 100% of the weighted hiring measure. The recession between 2014-2016 reduced the weighted hiring measure by 30%. Each dot is estimated separately, using as the outcome variable whether the student has already graduated in semester  $\tau$  relative to expected graduation (cumulative graduation measure). The dots are the estimates, and the lines represent the 95% confidence intervals. Standard errors are clustered at the major and state levels (*two-way clustering*). All regressions include fixed effects for program, time of admission, fall semester, and demographic cells (gender, race, and age).

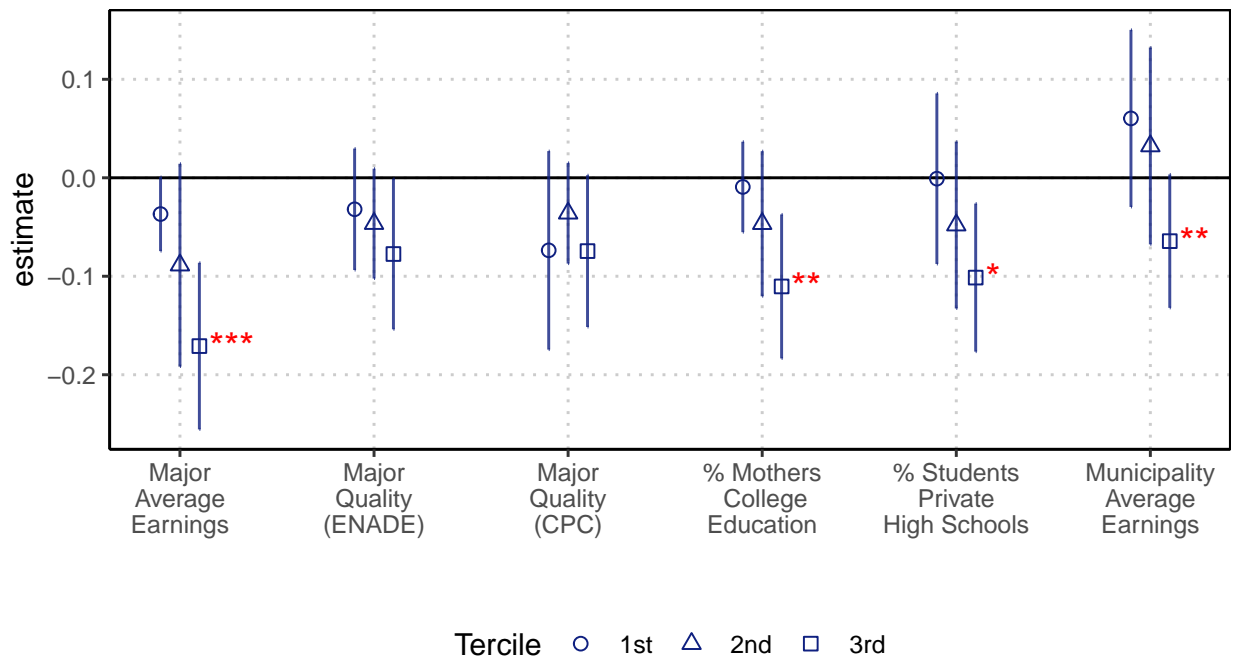
hiring rate increases the average duration by 0.0037 semesters. The 30% decrease in hiring observed in the 2014-2016 regression implies a 0.112 increase in average college duration, 1 out of 9 students delaying by one semester, or 1 out of 18 students delaying graduation by one year. In the Appendix A.2, I also obtain this number directly using a Tobit regression, where the outcome is the censored semester of actual graduation. Due to computation limitations, I cannot include the full set of fixed effects used in the benchmark results. The estimate is very close, indicating an increase of 0.0035 semesters for a 1% decrease in the hiring rates.

## 6.2 Heterogeneity

In this section, I investigate heterogeneities of the main effect of delaying graduation when facing a more depressed labor market for students in public universities. Figure 7 presents several of these exercises. The first shows the heterogeneous effects according to

the average major earnings tercile. The average major earnings were computed using the total earnings for all individuals in a given major using the Demographics Censuses in 2000 and 2010, net from gender, race, and age effects.<sup>22</sup> We can see that students in majors with higher predicted earnings are more likely to delay graduation. The two red stars close to the coefficient for the third tercile shows that we can reject, at 5% level, that  $\beta_{3rd\ Tercile} = \beta_{1st\ Tercile}$ . In Appendix Figure A.4 I compute the effect for each major separately.

Figure 7: Heterogeneity



Notes: The figure plots the estimation of  $\beta$  from equation 3 for students in public universities interacted with terciles for each variable. I multiply the coefficient by minus one, therefore, we can see the coefficients as a decrease of 100% of the weighted hiring measure. The recession between 2014-2016 reduced the weighted hiring measure by 30%. Each group of heterogeneity is estimated separately. The circles are the effects for the 1st tercile, the triangles for the 2nd, and the squares for the 3rd tercile. The circles, triangles, and squares are the estimates, and the lines represent the 95% confidence intervals. Standard errors are clustered at the major and state levels (*two-way clustering*). All regressions include fixed effects for program, time of admission, fall semester, and demographic cells (gender, race, and age). The red stars represent the p-values of the tests for whether the effects for the second and third terciles are the same as the one for the first tercile. 3 stars are used for p-values inferior a 1%, 2 starts for 5%, and 1 star for 10%.

In the next two sets of results, I compute heterogeneity across two quality measures, the

<sup>22</sup>I use the total earnings of individuals between 25 and 65 years that graduated for each major, pooling data from the Demographic Census in 2000 and 2010. I first residualized earnings on gender, race, and age fixed effects.

first using the average scores of the graduating students in the ENADE exam and the second a measure of quality computed by the Ministry of Education (CPC). Using the average score of graduating students at ENADE, we see weak evidence that students in better programs are more likely to delay in response to a labor market shock. We do not see the same ordering across the three terciles using the CPC measure.

The last three results turn to the socioeconomic conditions and proxies for family resources. We can see that students in majors with a higher proportion of mothers with college education and a higher proportion of students from private high schools exhibit larger effects. In both cases, we reject that the effects for the third tercile are the same as for the first tercile. The last result splits students by the average municipality earnings, computed with the same procedure as the major average earnings. We can see that students born in richer municipalities exhibit larger effects.

Table 4 presents two more heterogeneities at the student level, by gender and race. We do not reject the null hypothesis that the effect for men and women are the same. We have a slightly smaller estimate for Black and Native students, which would be consistent with the heterogeneity results at the program level. However, we do not reject that those coefficients are the same. Moreover, the exercise by race needs to be analyzed with care due to the high level of missingness for this variable (between 35-40%).

### **6.3 Robustness**

In this section, I explore other threats to my identification strategy and the results' robustness. Figure 8 presents the results of several robustness exercises. The first dot shows the point estimate of the benchmark result with a line segment representing the 95% confidence interval.

One concern with my strategy is due to the fact that employment conditions are corre-

Table 4: Heterogeneity by gender and race

<i>Outcome:</i>	<i>On-time graduation</i>		p-value
	(1)	(2)	
	Men	Women	$(\beta_{\text{Men}} = \beta_{\text{Women}})$
Effect	-0.080	-0.074	p-value
(s.e.)	(0.032)	(0.033)	{0.555}
[p-value]	[0.020]	[0.037]	
	White/Asian	Black/Native	$(\beta_{\text{White/Asian}} = \beta_{\text{Black/Native}})$
Effect	-0.057	-0.047	p-value
(s.e.)	(0.041)	(0.029)	{0.753}
[p-value]	[0.179]	[0.115]	

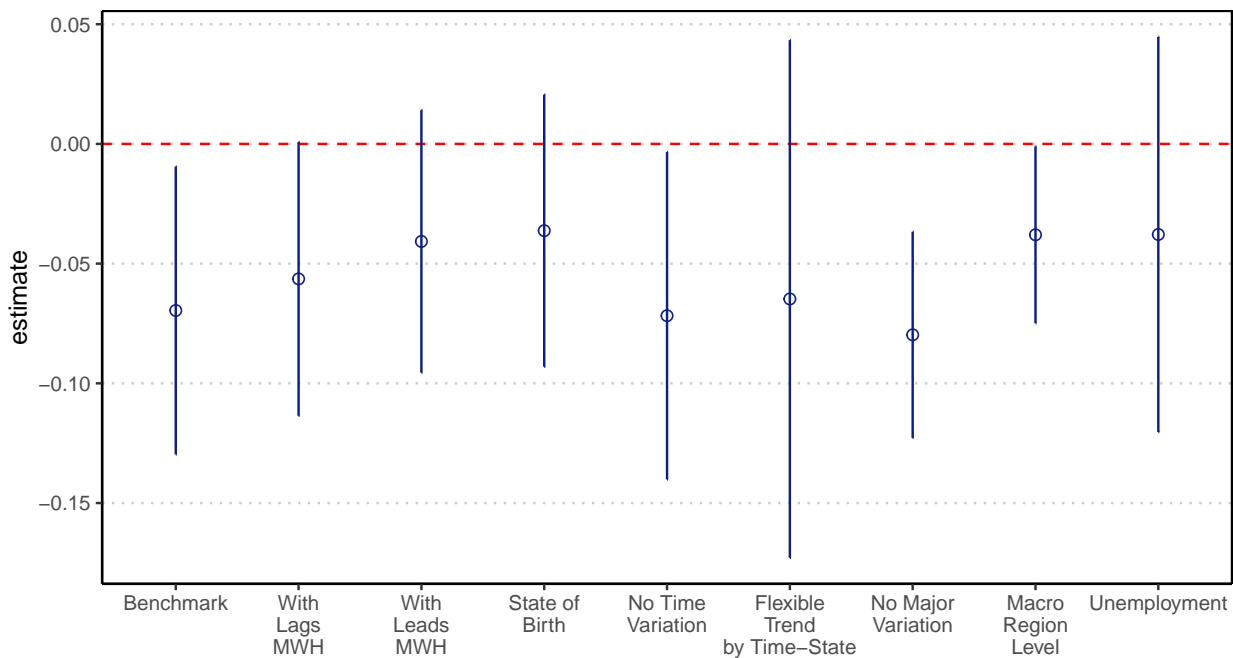
Notes: The table presents the estimation of  $\beta$  from equation 3 for students in public universities interacted with gender and race. I multiply the coefficient by minus one, therefore, we can see the coefficients as a decrease of 100% of the weighted hiring measure. The recession between 2014-2016 reduced the weighted hiring measure by 30%. Each group of heterogeneity is estimated separately. Standard errors are clustered at both the major and state levels (*two-way clustering*). All regressions include fixed effects for program, major-admission time, fall semester, and demographic cells (gender, race, and age). The third column shows in brackets the p-value of the test whether the effect for men is the same for women (first row) and the effect for White/Asian is the same for Black/Native students (second row).

lated over time. Facing a worse labor market near expected graduation could also imply that the student also faced worse labor market conditions during their college studies. Therefore, what I interpret as students avoiding entering a depressed labor market could instead be students not being able to graduate because of bad shocks in the labor market interacting with their proficiency in the program, affecting their failure rate and, therefore, their credit accumulation. First, while this alternative mechanism could be plausible, it is not consistent with the heterogeneities I found in Section 6.2; the interactions of bad labor market shocks with student performance would imply larger effects for students with lower socioeconomic status and fewer family resources, while I found the exact opposite. Nevertheless, I augment specification 1, including lagged hiring variable for up to 3 years, spanning the entire period



most of the students are in college in my sample. The result is the second position in Figure 8, showing a very similar effect. In a similar concern, it could be the case that students are responding to future labor market conditions and not the conditions at the moment of graduation as I interpret them. The third result includes leads of the variable of interest for the next 3 years, yielding, nevertheless, a very similar result.

Figure 8: Robustness



Notes: The figure plots the estimates of  $\beta$  from equation 3 for students in public universities. I multiply the coefficient by minus one, therefore, we can see the coefficients as a decrease of 100% of the weighted hiring measure. The recession between 2014-2016 reduced the weighted hiring measure by 30%. The circles are the point estimates, and the lines represent the 95% confidence interval. Standard errors are clustered at the major and state levels (*two-way clustering*). Each circle is a different robustness exercise detailed in the main text.

The strategy employed in this paper explores spatial variation on employment using the state where students are expected to graduate, as is commonly employed in the existing literature. However, it could be the case that students sort into colleges depending on the labor market conditions, which would violate my identification strategy. I replace the MWH for the state of birth of students and not the state where the institution is. This is the fourth result in Figure 8, where I obtain a slightly smaller estimate.

The main specification includes admission time fixed effects. The idea is to control for the trends in higher education enrollment in Brazil. In the main results, we saw that these results look the same if we include a more parsimonious quadratic trend instead of the fully flexible fixed effects. The fifth result shows that even if I completely eliminate any use of time variation by including graduating semester fixed effects, I would obtain similar results. The following result also relaxes the trend assumption by further interacting the major-admission time fixed effects with states. There is a significant loss of precision since comparisons across states are eliminated.

My labor market measure benefits from adding variations in majors, while most common approaches only consider time and spatial variations. However, it adds additional complexity to computing the weights for each major-occupation. I compute the weights, pooling the two Population Censuses with more than 30,000 surveyed individuals.<sup>23</sup> Nevertheless, some weights could be measured with error. In the eighth result in figure 8, I use the hiring measure obtained without majors, obtaining a very similar result.<sup>24</sup> The following result computes hiring at the macro-region level instead of states. Brazil has 135 macro-regions, which subdivide the 27 states. This approach has the advantage of being more local and bringing more variation to the estimation. However, it can also bring more measurement error since the labor market in consideration can span different macro-regions for several students.

The last result computes the same specification using as the labor market measure the unemployment rate in each state. In order to yield comparable estimates, I multiply the unemployment rate by the according variation of hirings between 2014 and 2016.<sup>25</sup> We can see that we obtain a similar result with this measure, with lower precision.

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<sup>23</sup>In the Demographic Census all individuals respond to a short survey, and a subset of households are selected to answer an expanded version of the questionnaire.

<sup>24</sup>I compute average hirings for each state for all employees with college degrees.

<sup>25</sup>Between 2014 and 2016, the average state unemployment rate rose 5.3 percentage points, while hirings fell by 30%.

In addition to this robustness, I conduct four extra exercises. First, as a placebo check, I run the main specification 1 using lagged values of the weighted hiring measures. The results are presented in the Appendix figure A.5. Using the 1-year lagged hiring measure, I still estimate a significant result, half of the magnitude of our benchmark estimate. Reassuringly, the estimates with more than two-year lags are fairly small and indistinguishable from zero. Second, the causal interpretation relies on the identification assumption that, conditional on our rich set of fixed effects, there are no unobserved factors correlated with the employment measure and on-time graduation. While this assumption is untestable, I show in the Appendix table A.5 that the demographics of students are not correlated with the employment measure. There is also a concern that the relationship between employment and on-time graduation is not linear. In Appendix Figure A.6, I first residualized both the outcome (on-time graduation dummy) and hiring measure on all the other variables in equation 1. I present ten bins with average residualized hiring measure and average residualized on-time graduation. We can see that all bins closely resemble the linear estimate. Lastly, I also show in the Appendix A.3 that the results are robust to changes in the sampling definitions and to excluding years where the data was linked over time using the matching algorithm.

## 6.4 Course credits and working while in college

While the Higher Education Census provides broad coverage of all students in higher education in Brazil, it does not include information about their course load towards completing the degree. I also do not have much information at the student level. I overcome these two issues by accessing detailed data from one large public university in the state of Bahia — the federal university of the state (flagship state university) UFBA. Unfortunately, this data comes from one state, so the hiring measure can only vary by time and major.

First, Table 5 shows the main results for this sample. In the first column, a 1% reduction

in the major-weighted hiring rate decreases the on-time graduation rate by 0.18 percentage points. This is larger than our estimates for public universities in the main sample. One of the advantages of this data is having more detailed information at the student level, for instance, we have the admission score for almost all students. The last three columns of Table 5 show the heterogeneity by admission score terciles, computed within each major-year. We can see that students at the top of the distribution exhibit large effects.

Table 5: UFBA — Main results

<i>Outcome:</i>	<i>On-time graduation</i>			
	Overall	by Admission Score Tercile		
		1st	2nd	3rd
Hiring	-0.181	-0.117	-0.216	-0.220
(s.e.)	(0.046)	(0.056)	(0.067)	(0.063)
[p-value]	[0.000]	[0.040]	[0.002]	[0.001]
N obs	41,475	34,477		

Notes: The table presents the estimation of  $\beta$  from equation 3 for the students at UFBA. I multiply the coefficient by minus one, therefore, we can see the coefficients as a decrease of 100% of the weighted hiring measure. The recession between 2014-2016 reduced the weighted hiring measure by 30%. The first column presents the overall result. In columns 2-4, I interact all variables with an indicator for the student admission score tercile (computed for each within program-year). Standard errors are clustered at the major level. All regressions include fixed effects for program, major-admission time, fall semester, and demographic cells (gender, race, and age).

Second, I evaluate the effect of additional credit accumulation for students who postpone graduation. On average, students graduate with 3,818 credits. Considering that the average course has 78 credits, this is equivalent to graduating with 48.9 courses. I use an instrumental variables approach where the endogenous decision of on-time graduation will be instrumented by the labor market conditions. For this analysis, I use the number of credits measured one year after expected graduation.

In the first column in table 6, I show the first stage estimates. For this sub-sample, a 1%

Table 6: UFBA — Credits completed (IV)

<i>Outcome</i>	First Stage	Second Stage
	<i>On-time graduation</i>	<i>Credits Completed</i>
Hiring (s.e.) {F-stat}	-0.245 (0.058) {17.867}	
On-time graduation (s.e.) [p-value]		-220.3 (331.6) [0.508]
N Obs	20,206	20,206

Notes: The table presents the two stage least squares estimates for the effects of on-time graduation on the number of credits obtained by graduates. I instrument the on-time graduation by the major-weighted hiring measure. In the first column we can see the first stage estimate (point estimate, standard errors and the F-statistic). The second column shows the second stage estimates. Standard errors are clustered at the major level. All regressions include fixed effects for program, time of admission, fall semester, and demographic cells (gender, race and age).

drop in the hiring rate decreases the on-time graduation rate by 0.24 percentage points. The F-statistic is 17.9. In the second column, I show the second stage estimate. The students induced to graduate on time have, on average, 220 fewer credits, which is equivalent to almost 3 courses.<sup>26</sup> The point estimate suggests that students use the delay to take extra courses. However, the results are too noisy to draw conclusions. In the Appendix Table A.6 I also show that the employment measure is not associated with lower credit accumulation in the first years of the program. In the semesters immediately before expected graduation, I observe that cohorts that experience a more depressed labor market have obtained fewer credits. While I do not reject that these estimates are different from zero, they may indicate the mechanism through which students delay graduation: by taking fewer courses in the semesters near expected graduation.

Finally, with the UFBA data, I can perform several heterogeneity analyses at the

<sup>26</sup>On average, students take 380 credits in a semester — which is equivalent to 4.9 courses. In the year of expected graduation, this number is smaller, around 4.2 courses.

individual level. I start with whether the student was working formally in the year before expected graduation. We can see in the first row of Table 7 that the effect is close to zero for students that were already working formally in the year before expected graduation. In contrast, those that were not working decreased their likelihood of on-time graduation by 0.228pp when facing a 1% decrease in the hiring rate.

Table 7: UFBA — Heterogeneity

	Hiring	Std Error	P-value	P-value Difference
<b>Working in Junior Year</b>				
Yes	-0.010	(0.081)	[0.907]	-
No	-0.228	(0.044)	[0.000]	{0.003}
<b>Public High School</b>				
Yes	-0.120	(0.053)	[0.026]	-
No	-0.313	(0.061)	[0.000]	{0.000}
<b>Mother Education Level</b>				
Less than High School	-0.106	(0.047)	[0.026]	-
High School	-0.190	(0.059)	[0.002]	{0.215}
Some College and more	-0.313	(0.063)	[0.000]	{0.001}
<b>Family Income</b>				
Level 1	-0.117	(0.052)	[0.028]	-
Level 2	-0.186	(0.062)	[0.003]	{0.256}
Level 3	-0.306	(0.054)	[0.000]	{0.003}

Notes: The table presents the estimates of  $\beta$  from equation 3 for students in UFBA interacted with several different variables. I multiply the coefficient by minus one, therefore we can see the coefficients as a decrease of 100% of the weighted hiring measure. The recession between 2014-2016 reduced the weighted hiring measure by 30%. Each group of heterogeneity is estimated separately. The first column shows the point estimates, the second column the standard error and the third column the p-value of the test whether the effect is different than zero. The fourth column presents the tests that each level of the heterogeneity analyzed is the same as the first one present in each group. Standard errors are clustered at the major level. All regressions include fixed effects for program, time of admission, fall semester, and demographic cells (gender, race and age).

In the next three sets of results in Table 7, I analyze proxies for socioeconomic status at the individual level. They all point to the same conclusion: slightly larger effects for the students with better socioeconomic status and more family income. We can see larger point estimates for those students with mothers with some college education or more who completed high school in public schools and with higher self-reported family income.

## 7 Conclusion

College students graduating in a recession face negative and persistent effects on their labor market careers. They initially match with smaller firms and in lower-earnings occupations, earning 10% less for up to 10 years after graduation (von Wachter, 2020). The adverse effects are not restricted to the labor market; individuals graduating in a recession experience worse health, adverse family outcome, and higher crime outcomes.

In this paper, I investigate whether college students delay graduation to avoid entering a depressed labor market. I explore variations in the labor market conditions over time, geography, and majors in Brazil. I find that students in public institutions are 2.1pp less likely to graduate on time when facing a recession that decreases new hires by 30%. This represents an increase in the average duration by 0.11 semesters, or 1 out of 18 students delaying by one year.

The delaying effects are more prominent for students with higher scores, in higher-earning majors, and from more advantaged backgrounds. This has important implications for inequality since students with better resources can better shield themselves from labor market fluctuations by controlling the time of graduation. The results show how the institutional setting is important when assessing the college students' response to the labor market conditions.

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# Online Appendices

## Appendix A - Additional Exercises

### A.1 Reweighting

Public and private institutions differ in several characteristics, such as course quality, selectivity, and student composition. In this exercise, I reweight the observations from the private institutions to have the same distribution as the students from the public universities. The first column of table A.1 shows the baseline result. In the second column, I reweight the observations from the private institutions to have the same distribution of majors as the public universities. The reweight procedure yields the same proportion of students in each major for every semester in the sample. The numbers of observations are slightly different because if no private universities are offering a major in a given semester, the students from public institutions from that major-year are dropped.

The third column reweights for the students' demographics jointly defined by gender, race, and age of entry. The fourth column matches the sample by comparing the proportion of students that studied in public high schools in a given program. For this exercise, I compute the proportion of students in public schools at every 5% (0-5%, 5-10%, 10-15%, ...,95%-100%). The last two columns reweight the distributions according to two measures of quality: the average score at the ENADE exam (5th column) and the CPC measure (6th column). In both cases, I computed qualities rounding at the one-digit level.

### A.2 Tobit Regression

I run a Tobit regression where the outcome is the censored semester of actual graduation. Therefore Student  $i$  that graduated on time will have  $Y_i = 0$ , while Student  $j$  that graduated 3 semesters after their expected graduation date will have  $Y_j = 3$ . A Student  $k$  that did not graduate until the maximum observed semester (for instance, 8) for their cohort

Table A.1: Reweighting

	<i>Outcome:</i>		<i>On-time graduation</i>			
	(1)	(2)	(3)	(4)	(5)	(6)
Reweighting for:	Benchmark	Majors	Demographics	% Students Public HS	Quality (ENADE)	Quality (CPC)
Hiring x Public (s.e.) [p-value]	-0.070 (0.031) [0.032]	-0.067 (0.033) [0.053]	-0.068 (0.033) [0.050]	-0.064 (0.036) [0.082]	-0.059 (0.035) [0.107]	-0.059 (0.035) [0.108]
Hiring x Private (s.e.) [p-value]	-0.003 (0.040) [0.934]	0.000 (0.032) [0.991]	-0.005 (0.035) [0.886]	0.000 (0.039) [0.995]	-0.016 (0.038) [0.676]	-0.016 (0.038) [0.683]
N Obs	4,058,758	4,016,188	4,058,743	3,452,328	3,600,588	3,596,268
p-value ( $\beta_{\text{public}} = \beta_{\text{private}}$ )	{0.084}	{0.058}	{0.099}	{0.159}	{0.350}	{0.352}
ratio ( $\beta_{\text{private}}/\beta_{\text{public}}$ )	0.048	0.006	0.075	0.004	0.273	0.267

Notes: The table presents the estimation of  $\beta$  from equation 3 interacted with an indicator for students belonging to a public or private institution. I multiply the coefficient by minus one, therefore, we can see the coefficients as a decrease of 100% of the weighted hiring measure. The recession between 2014-2016 reduced the weighted hiring measure by 30%. The first column presents the baseline result from Table 3. Each of the following columns reweights the observations from the private institutions to have the same distribution as the public universities according to a different dimension. The reweighting procedure is described in the Appendix A.1. Each exercise is computed separately. Standard errors are clustered at both the major and state levels (*two-way clustering*). All regressions include fixed effects for program, major-admission time, fall semester, and demographic cells (gender, race, and age). The last but one row shows the p-value testing whether the effect is the same for public and private institutions. The last row shows the ratio of the point estimates for public and private effects.

will have the *censored*  $Y_k = 8$ .

I cannot run the equivalent of equation 1 because I do not have enough computational power to include the thousands of fixed effects present in my baseline specification. Instead, I run the following specification:

$$Y_i = MW H_{t_1(i),m(i),s(i)} + \eta_{t_0(1)} + \nu_{s(i)} + \gamma X_i + \delta Z_{p(i)} + \varepsilon_i$$

In this specification, I substitute the program fixed effects with both state fixed effects and program characteristics (major, schedule, duration, and others). The results of the

Tobit regression are presented in the table A.2 below. Another limitation is the estimation of standard errors, which can be done only for one cluster variable. I chose to estimate with the state level because it is the variable with the lowest number of groups (compared to the number of majors).

Table A.2: Censored regression

	<i>Outcome: Semester of graduation</i>	
	(1)	(2)
Hiring	0.455	0.353
(s.e.)	(0.504)	(0.508)
[p-value]	[0.367]	[0.488]
Num.Obs.	1,260,875	1,024,315
Admission year FE	✓	✓
State FE	✓	✓
Demographics	✓	✓
Major FE	✓	✓
Schedule and Duration	✓	✓
Program Characteristics	-	✓

Notes: Tobit regression using as the outcome the censored semester of graduation relative to expected graduation for students in public universities. I multiply the coefficient by minus one, therefore, we can see the coefficients as a decrease of 100% of the weighted hiring measure. The recession between 2014-2016 reduced the weighted hiring measure by 30%. Each group of heterogeneity is estimated separately. Standard errors are clustered at the state level. Each column differs only by the set of included controls.

### A.3 Sensitivity Analysis

In order to reliably compute the major-weighted hiring measure, I apply some sampling restrictions. I detail each of them below:

1. **RAIS tolerance (20%)** — First, I drop occupation codes whose maximum error rate across all years between 2003-2019 are above 20%. This is likely to indicate issues with the structure of the coding scheme of occupation to have changed in my sampling period.

2. # observations in each Census (20) — I only keep majors that I observe at least 20 individuals working in each of the Demographic Censuses (2000 and 2010).
3. % Observed (30%) — I drop majors that I only observed fewer than 30% of the individuals working in occupations that were not discarded in procedure 1 above.
4. Maximum Age (40) — I only use individuals aged between 20 and 40 to compute the occupation weights in order to capture occupations that are relevant for recent college graduates.

Table A.3 below assess how the baseline result changes when we vary each of the above-specified thresholds. We can see that the main results are not sensitive to any sampling decision. The table also presents the effective number of majors and occupations and the percentage of employment covered for each sampling decision.

Table A.3: Sensitivity Analysis

<i>Outcome: On-time graduation</i>									
	Benchmark	RAIS tolerance		# obs Census		% observed		Max Age	
	-	0.15	0.25	0	40	0.00	0.50	35	45
Hiring x Public (s.e.) [p-value]	-0.070 (0.031) [0.032]	-0.051 (0.026) [0.059]	-0.073 (0.032) [0.029]	-0.069 (0.030) [0.031]	-0.070 (0.031) [0.032]	-0.091 (0.036) [0.019]	-0.061 (0.028) [0.035]	-0.072 (0.031) [0.031]	-0.069 (0.030) [0.032]
Hiring x Private (s.e.) [p-value]	-0.003 (0.040) [0.934]	-0.011 (0.040) [0.775]	-0.004 (0.039) [0.917]	-0.003 (0.040) [0.935]	-0.004 (0.040) [0.920]	-0.018 (0.044) [0.683]	-0.005 (0.040) [0.899]	-0.003 (0.039) [0.944]	-0.004 (0.040) [0.926]
N Obs	4,058,758	2,811,362	4,124,702	4,071,642	4,051,776	4,653,332	3,895,403	4,056,786	4,058,758
# of Majors	64	55	65	79	62	69	62	63	65
# of Occupations	143	106	150	143	143	143	143	143	143
% employment	0.925	0.725	0.941	0.925	0.925	0.925	0.925	0.925	0.925

Notes: The table presents the estimation of  $\beta$  from equation 3 interacted with an indicator for students belonging to a public or private institution. I multiply the coefficient by minus one, therefore we can see the coefficients as a decrease of 100% of the weighted hiring measure. The recession between 2014-2016 reduced the weighted hiring measure by 30%. The first column presents the baseline result from Table 3. Each of the next columns reestimate our main regression with a sample that was computed varying of my sampling decision rules. Each exercise is computed separately. Standard errors are clusters at both the major and state levels (*two-way clustering*). All regressions include fixed effects for program, time of admission, fall semester, and demographic cells (gender, race and age).

I also compute the main results excluding the years where the individual information was linked over time using the matching algorithm instead of the unique identifiers. Table

A.4 below presents these results, that are really similar to the main results presented in the table 3.

Table A.4: Results restricting the data to years that unique identifiers are observed

<i>Outcome:</i>	<i>On-time graduation</i>					
	(1)	(2)	(3)	(4)	(5)	(6)
Hiring	-0.012 (0.021) [0.585]					
Hiring x Public		-0.060 (0.028) [0.043]	-0.053 (0.028) [0.066]	-0.053 (0.028) [0.070]	-0.059 (0.032) [0.072]	-0.048 (0.027) [0.092]
Hiring x Private		0.004 (0.030) [0.905]	0.010 (0.025) [0.684]	0.013 (0.024) [0.586]	-0.006 (0.032) [0.858]	0.007 (0.029) [0.800]
N Obs	3,121,188	3,121,188	3,121,188	3,121,188	3,121,188	3,121,188
p-value ( $\beta_{\text{public}} = \beta_{\text{private}}$ )	-	{0.100}	{0.022}	{0.028}	{0.113}	{0.101}
Major-State FE	✓	✓	-	-	-	-
Program FE	-	-	✓	✓	✓	✓
Demographics	-	-	✓	✓	✓	✓
Time Trend	Quadratic	Quadratic	Quadratic	Quadratic	Admission Time FE	Major-Admission Time FE

Notes: The table presents the estimation of  $\beta$  from equation 3 for the data restricted to the year 2017 that does not rely on the matching algorithm to follow students. I multiply the coefficient by minus one, therefore, we can see the coefficients as a decrease of 100% of the weighted hiring measure. The recession between 2014-2016 reduced the weighted hiring measure by 30%. The first column presents the overall results. In columns 2-6, I interact all variables with an indicator of whether the students belong to a private or public institution. Columns 2-6 differ in the set of control variables included in each specification. Standard errors are clustered at both the major and state levels (*two-way clustering*). The p-value of the test whether the effect for public and private institutions are the same is provided for each specification. FE stands for fixed effects.

## Appendix B - Data

### B.1 Higher Education Census

I use all the Higher Education Census (*Censo da Educação Superior*) from 2009 to 2019. From 2009 to 2017, the data includes unique identifiers at the student and enrollment level, allowing me to follow individual students over time. For 2018 and 2019, these identifiers are suppressed from the public files.

I develop an algorithm to match students across time using the information on the university, major, first enrollment year, date of birth, gender, and place of birth when this information yields a unique observation. To test the algorithm, I apply it to the years before 2017, and I obtain a success rate between 91.7% and 94.3%. Notably, out of the 5.7%-8.3% not successfully matched, less than 0.01% are from two distinct students being incorrectly matched. The majority of them are students that I do not attempt to match because they do not have unique observations across the variables used in the algorithm. I always match only two consecutive years to maximize the algorithm's success rate.

After obtaining the unique identifiers for the entire period, I define enrollment as a combination of student-university-major. The enrollment date and schedule are obtained from the first time they appear in the data.<sup>27</sup> I obtain personal information for each student, including date of birth, gender, race, and place of birth as the mode for each variable across all years.

I then apply several cleaning procedures to result in a homogeneous sample. I start with a universe of 40 million unique enrollments from 30 million students. I then drop observations where I could not obtain key characteristics from their programs. I lose 29% of students in this step, mainly those who first enrolled much earlier than 2009. I drop

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<sup>27</sup>Some years have missing data for the period of study. In these years, I consider the first non-missing information.

students that are not enrolled in B.A. equivalent programs (7.9%), not enrolled in in-person programs (0.05%), with no well-defined duration (0.6%), and with first enrollment before 2004 (0.6%).<sup>28</sup> Lastly, I drop students that were not between 17 and 22 years old when they first enrolled, dropping 23.2% of the sample and with expected graduation after 2019 (dropping 11.5%). The final sample has 7.8 million unique students, 9.5 million enrollments in 2,342 institutes, 74 majors, and 40,849 programs (major-institution-schedule).

## B.2 UFBA

I obtain panel data from all students enrolled in the university between 2003 and 2017 from the Federal University of Bahia (UFBA). In the cleaning procedure, I discard duplicated observations at the student-semester-course-status level, and I remove the fall of 2004 coursework since all classes were repeated in the spring due to a strike.

The initial data set covers 80,165 unique students. I remove students with conflicting data for the admission date (0.001%), that I cannot obtain information on the program (1.6%), with expected graduation after 2019 (20.2%), and in programs with less than 3-year duration (0.5%). The resulting sample has 62,245 unique students enrolled in 230 programs (major-schedule).

For every semester, I check whether students were working in the matched employer-employee data set, classifying “working” as having worked for at least one month during the semester.

## B.3 Household Surveys (PNAD and PNADC)

I use the Brazilian National Household Survey (PNAD, *Pesquisa Nacional por Amostra de Domicílios*) from 2002-2009 and 2011, and the Continuous Brazilian National Household Survey (PNADC, *Pesquisa Nacional por Amostra de Domicílios Contínua*) from 2012-2019,

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<sup>28</sup>The minimum duration of a bachelor’s course is three years, according to Ministry of Education Resolution 2 from 2007.



to compute the state unemployment rate. I restrict the sample to individuals aged 27 and 65 and estimate the unemployment rate using the sampling structure of the surveys (strata and sampling weights).

#### **B.4 Demographic Population Census**

I use data from the two demographic censuses in 2000 and 2010 (*Censo Demográfico*) throughout my analysis. First, I use the 2010 Census to obtain the state unemployment rates, with the same sampling restrictions as in the household surveys.<sup>29</sup>

I also use the two censuses to obtain the occupation-major weights. To ensure that I am calculating these weights according to the market new graduates face, I restrict the sample to working, college-educated 20-40-year-olds. I drop majors with less than 20 individuals working in any of the two Censuses or where more than 70% of individuals work in occupations not covered in the study. These restrictions remove 20 majors from the 84 majors listed. I obtain the weights taking into account the Census sampling weights.

Lastly, I use the two censuses to obtain the average earnings of each major, considering individuals between 27 and 65 years old, working, and with a college degree in a given major. I also obtain the non-major-specific average earnings for each municipality using all working individuals aged 27-65 years. I use the total labor earnings deflated by the consumer price index (IPCA) for both measures. I remove composition effects by residualizing earnings from gender, race, and age.

#### **B.5 Matched Employer-employee (RAIS)**

For most of the analysis, I use the public version of the matched employer-employee data, available in the data-leak *Base dos Dados*.<sup>30</sup> from 2003-2019. I restrict the sample to individuals between 27 and 65 years of age. There were initially 176 occupations at the

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<sup>29</sup>In the year that the demographic census is collected, the household surveys are not collected.

<sup>30</sup><https://basedosdados.org>

4-digit code level. I remove occupations that are likely to be affected by the modifications in the occupation codes between 2008-2012. In order to assess that, I compute the stock of employees working in a given occupation on December 31st of year  $t$  ( $\text{stock}_t$ ). I then compute the flow of employees in this occupation (hires - layoffs) in January of  $t + 1$  ( $\text{flow}_{t+1}$ ) and the stock of employees at the end of this month — ( $\text{stock}_{t+1}$ ). In the absence of codification changes and measurement errors, we expect:

$$\text{stock}_{t+1} = \text{stock}_t + \text{flow}_{t+1}$$

I compute the maximum proportion error for each occupation  $o$  as

$$\text{Max}_o = \max_t \left\{ \left| \frac{\text{stock}_{t+1}^o - \text{flow}_{t+1}^o}{\text{stock}_t^o} \right| \right\}$$

I then drop occupations whose maximum error is above 20% for any given year.

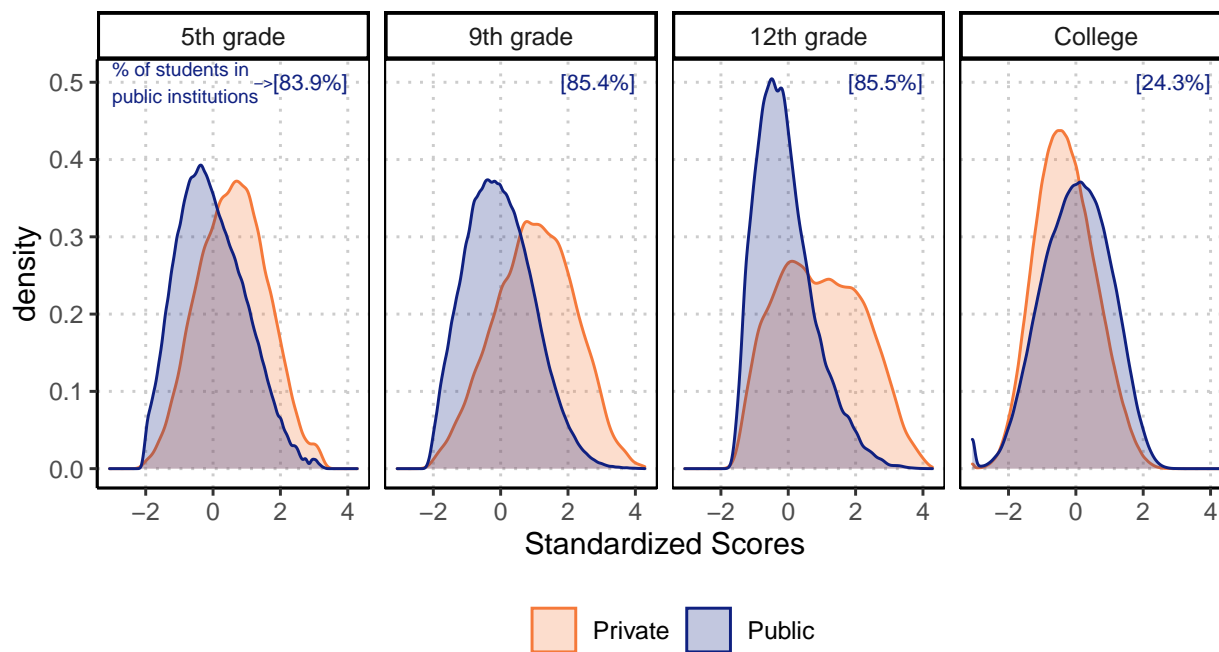
For the UFBA data, I use the restricted identified version of the data, available for 2003-2018, and I apply a similar procedure.

## B.6 ENADE

I obtain the ENADE (*Exame Nacional de Desempenho dos Estudantes*) data from 2004 to 2019. I restrict the sample to individuals who answered at least one question from those I selected (working status, parents' educational level, type of high school). I remove programs in which, across all years, there were fewer than 30 valid responses or fewer than 50% of students had valid answers. For the ENADE and CPC scores, I use the final scores released by the INEP agency.

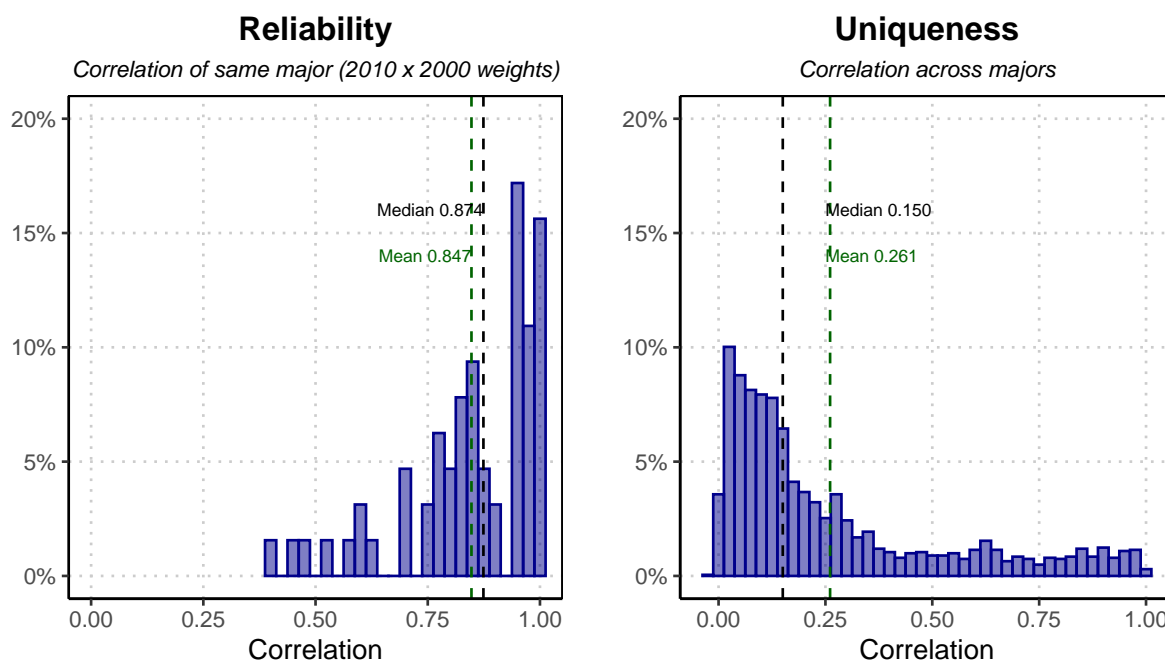
## Appendix C - Appendix Table and Figures

Figure A.1: Distribution of scores by public and private schools



Notes: The figure shows the density of standardized scores for public (in blue) and private schools (in orange). The scores for students in 5th, 9th, and 12th (3rd grade of High School) grades were obtained from the national SAEB exam in 2015. The grades for college students use the ENADE exam between 2014-2016. All scores were normalized to have zero mean and one standard deviation for the public schools. The numbers in brackets show the proportion of students in public schools/universities.

Figure A.2: Occupation-major weights - Reliability and uniqueness



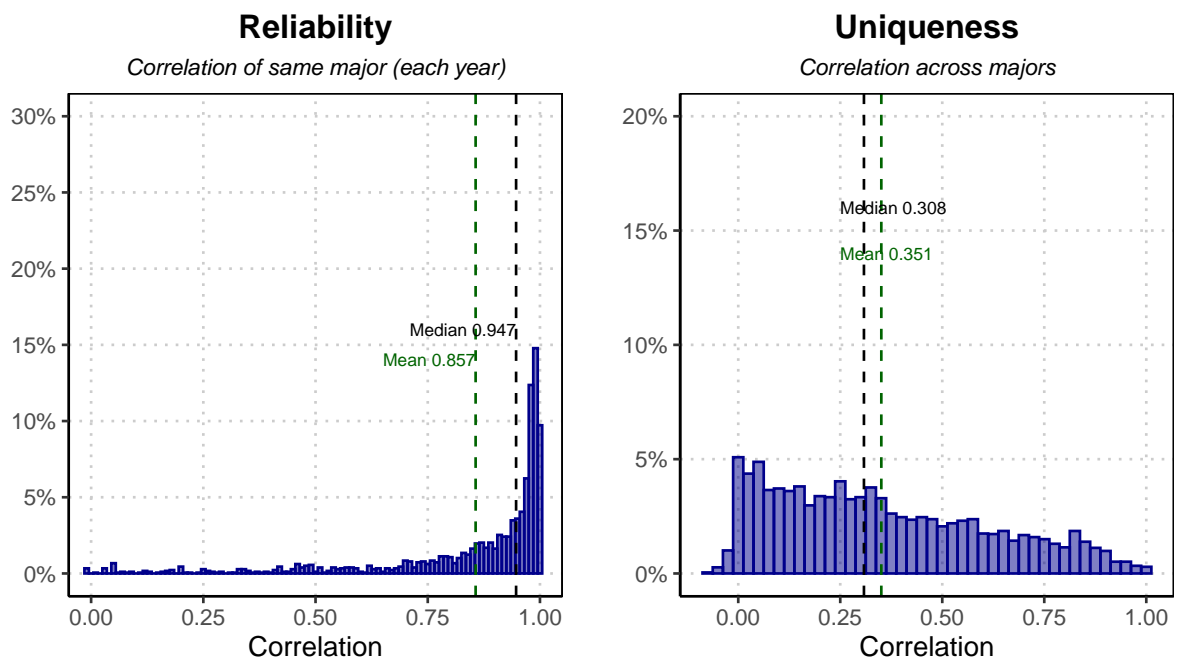
Notes: The panel on the left shows the histogram for the correlation of the vector of weights in 2000 and 2010 for the same major in the main sample. The vertical **black** line shows the median value and the **green** line the mean. The panel on the right shows the histogram for the comparison of the vector of weights across different majors.

Table A.5: Balance

<i>Outcome:</i>	Women	Black/Native	Age at Entry
	(1)	(2)	(3)
Hiring	-0.001	0.003	0.075
(s.e.)	(0.007)	(0.023)	(0.052)
[p-value]	[0.931]	[0.913]	[0.160]
N Obs	4,058,758	2,552,777	4,058,758

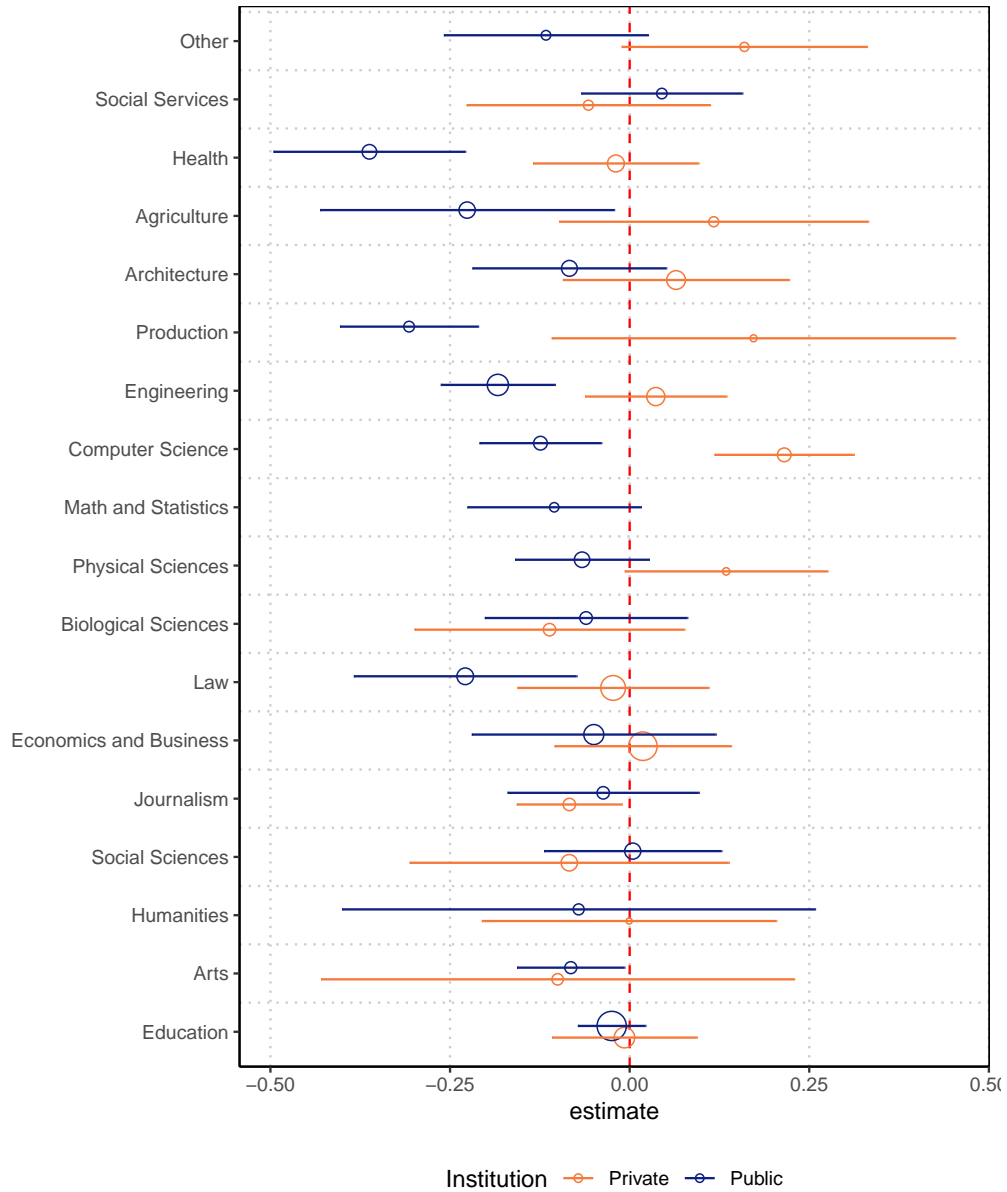
Notes: The table presents the estimation of  $\beta$  from equation 3 for the following outcomes: indicator for women, indicator for Black-/Native and age at admission. I multiply the coefficient by minus one, therefore we can see the coefficients as a decrease of 100% of the weighted hiring measure. The recession between 2014-2016 reduced the weighted hiring measure by 30%. Standard errors are clustered at both the major and state levels (*two-way clustering*). All regressions include fixed effects for program, major-admission time, and fall semester.

Figure A.3: Occupation-major weights - reliability and Uniqueness (UFBA sample)



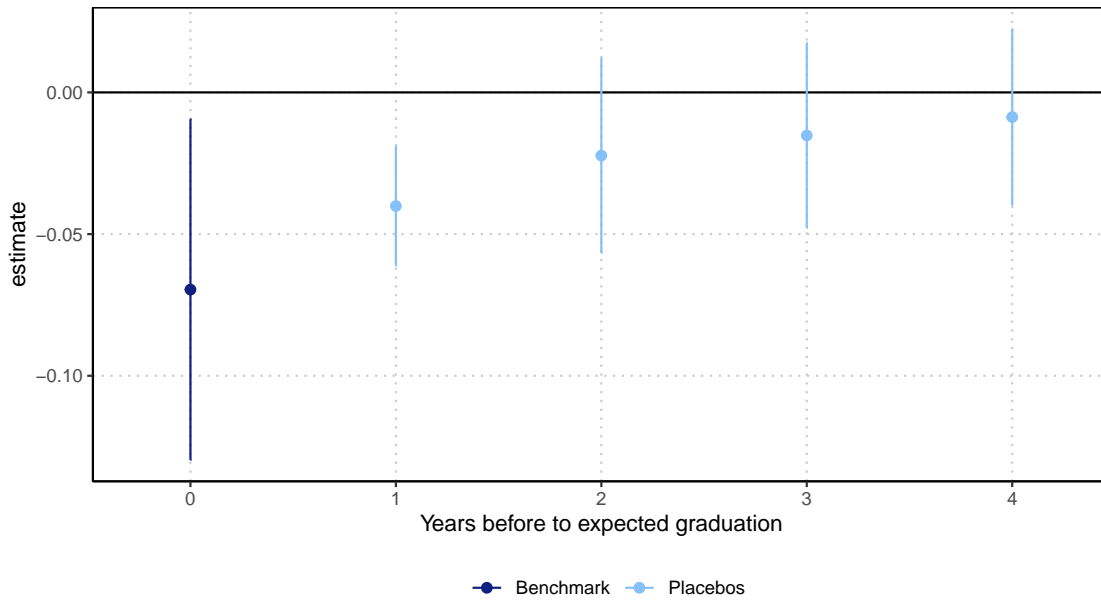
Notes: The panel on the left shows the histogram for the correlation of the vector of weights in different years for the same major in the UFBA sample. The vertical **black** line shows the median value and the **green** line the mean. The panel on the right shows the histogram for the comparison of the vector of weights across different majors.

Figure A.4: Heterogeneity by Major



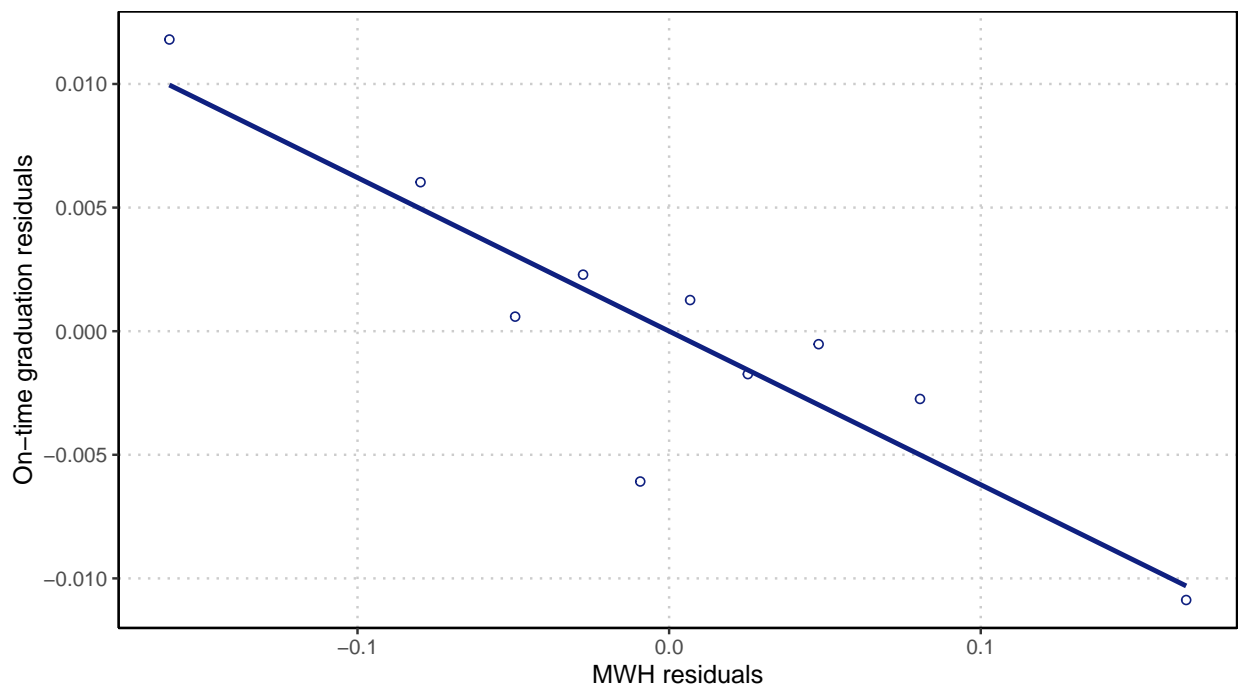
Notes: The figure presents the estimation of  $\beta$  from equation 3 interacted with an indicator for students belonging to a public or private institution and major groups. I multiply the coefficient by minus one, therefore, we can see the coefficients as a decrease of 100% of the weighted hiring measure. The recession between 2014-2016 reduced the weighted hiring measure by 30%. The circles represent the point estimates, and the lines the 95% confidence intervals. Standard errors are clustered at the major and state levels (*two-way clustering*). All regressions include fixed effects for program, time of admission, fall semester, and demographic cells (gender, race, and age). The orange color represents estimates for private institutions and blue color for public universities. All majors with at least 1,000 students are displayed in the figure.

Figure A.5: Placebo Effects



Notes: The figure presents the estimation of  $\beta$  from equation 3 for students in public universities. I multiply the coefficient by minus one, therefore, we can see the coefficients as a decrease of 100% of the weighted hiring measure. The recession between 2014-2016 reduced the weighted hiring measure by 30%. The circles represent the point estimates, and the lines the 95% confidence intervals. Each regression uses the major-weighted hiring measure for  $\tau$  years before the expected graduation, for  $\tau \in [0, 4]$ . Standard errors are clustered at the major and state levels (*two-way clustering*). All regressions include fixed effects for program, time of admission, fall semester, and demographic cells (gender, race, and age).

Figure A.6: Residualized On-time Graduation and MWH



Notes: The circles represent the binned averages of the residualized on-time graduation dummy and the residualized major-weighted hiring measure, dividing the sample into 10 equal-sized groups ordered by the hiring measure residuals. The residuals are obtained regressing each variable on the full set of fixed effects (semester, program, time of admission, and demographic cells — gender, race, and age). The line is the slope ( $\beta$  coefficient from equation 1) of the benchmark OLS specification.



Table A.6: UFBA — Credits obtained before graduation

	<i>Outcome:</i>		<i>Credits Obtained</i>		
Semesters before expected graduation:	5	4	3	2	1
Hiring x 1st T	13.704	-33.940	-63.994	-88.143	20.258
(s.e.)	(10.485)	(54.134)	(66.991)	(80.308)	(119.263)
[p-value]	[0.194]	[0.532]	[0.342]	[0.275]	[0.865]
Hiring x 2nd T	42.736	62.531	-26.726	-77.691	-102.736
(s.e.)	(35.096)	(35.366)	(76.511)	(62.047)	(101.729)
[p-value]	[0.226]	[0.080]	[0.728]	[0.214]	[0.315]
Hiring x 3rd T	39.303	98.585	-17.948	-93.984	-149.203
(s.e.)	(34.327)	(40.891)	(59.259)	(51.829)	(103.254)
[p-value]	[0.255]	[0.018]	[0.763]	[0.073]	[0.152]
N Obs	32,507	34,635	35,868	36,487	36,487

Notes: The table presents the estimation of  $\beta$  from equation 3 interacted with an indicator for students admission score tercile (computed within program-year) for students in UFBA. I multiply the coefficient by minus one, therefore we can see the coefficients as a decrease of 100% of the weighted hiring measure. The recession between 2014-2016 reduced the weighted hiring measure by 30%. In each column the outcome variable is the total number of credits obtained in semester  $\tau$  relative to expected graduation, where  $\tau \in [1, 5]$ . Standard errors are clustered at both the major and state levels (*two-way clustering*). All regressions include fixed effects for program, time of admission, fall semester, and demographic cells (gender, race and age).