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Review

Dropping out of university in response to the COVID-19 pandemic

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ABSTRACT

This study empirically examines the impact of the COVID-19 pandemic on university students' enrollment behaviors using a comprehensive database of university enrollments from 2012 to 2022. Our analysis reveals a 3.7% decline in the probability of re-enrollment for the subsequent academic year among the first cohort affected by the pandemic. This effect is particularly pronounced among students entering university, as well as among non-free lunch students, international students, and male students. The medium-term analysis indicates that the pandemic led to a significant shift in enrollment behaviors, decreasing the likelihood of enrolling in subsequent years and reducing graduation rates two years after the pandemic. Moreover, we find that exposure to stricter lockdown policies led to a 3.8% decrease in enrollment behaviors. We investigate three potential mechanisms: (i) exposure to the pandemic, (ii) labor market opportunities, and (iii) university quality. However, we find little evidence to support that these factors are significantly associated with changes in enrollment behaviors. These findings contribute to our understanding of the disruptive consequences of the COVID-19 pandemic on students' educational trajectories and highlight its lasting impact on enrollment behaviors.

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1. Introduction

Each year, students face a critical decision regarding their higher education, as they weigh opportunity costs against anticipated labor market benefits. This decision is closely linked to students' perceptions of labor market outcomes, which are significantly influenced by external shocks such as financial crises, business cycles, and pandemics (Adamopoulou & Tanzi, 2017; Aucejo, French, Araya, & Zafar, 2020; Blom, Cadena, & Keys, 2021). Examining the impact of such extreme events on students' educational trajectories is crucial because they often exacerbate existing societal inequalities (Atkinson & Morelli, 2011; Stantcheva, 2022). The COVID-19 pandemic provides an ideal context to investigate this issue, given its profound and likely enduring effects on educational outcomes, including learning (Alan & Turkum, 2023; Betthäuser, Bach-Mortensen, & Engzell, 2023; Svaleryd & Vlachos, 2022; Werner & Woessmann, 2023). However, the extent to which the pandemic has affected students' enrollment decisions remains largely unexplored.

This study aims to examine the impact of the COVID-19 pandemic on university student dropout rates in France by analyzing changes in patterns of re-enrollment for the last decade. We hypothesize that external shocks like the pandemic may increase the likelihood of university student dropout. Using comprehensive administrative data on student enrollment status from 2012 to 2022, we investigate the enrollment decisions of 15,600,845 choices. Our findings indicate that the COVID-19 cohort showed a decreased propensity for re-enrollment in the subsequent academic year, with significant variations across fields and years of study, and student socioeconomic characteristics. We show that the impact of the pandemic induces a medium-term decrease in enrollment and graduation rate, that is likely to translate into structural changes in applications and enrollment behaviors. Finally, we find that being exposed to a one month heightened lockdown decreased student enrollment behaviors of about 3.8%. We then assess three potential mechanisms: (i) local exposure to the pandemic, (ii) local opportunity to the labour market, and (iii) university quality. We do not find evidence supporting these three mechanisms.

The rationale behind our approach stems from the understanding that students' decision-making is adaptable and susceptible to external shocks. These disruptions, ranging from economic crises (e.g., Grenet, Grönqvist, Hertegård, Nybom, & Stuhler, 2024) to health changes, can alter one's perception of future prospects, leading to stronger present-bias behaviors. This hypothesis is supported by studies linking exposure to natural disasters with adverse educational outcomes (Di Pietro, 2018) and correlating changes in labor market attractiveness with graduation likelihood (Adamopoulou & Tanzi, 2017). Our core hypothesis posits that students responded to the COVID-19 pandemic by dropping out of university, driven by lockdown policies that reduced labor market opportunities and the mental burden of the pandemic that hindered academic pursuit. These mechanisms influence students' decision-making regarding future economic benefits and the mental costs associated with continued education. Therefore, students

exposed to severe pandemic conditions and poor market opportunities are expected to be more likely to drop out.

Our data have several distinct characteristics that enable us to investigate the impact of the COVID-19 pandemic on university students' re-enrollment decisions while considering a wide range of individual factors. First, our data comprehensively capture students' enrollment choices from 2012 to 2022, allowing us to track student trajectories within the French higher education system in detail. Second, our data allow us to distinguish between changes in grading practices and individual decisions to discontinue studies at higher education institutions. Third, our data include information on both students' geographical locations and local variations in COVID-19 transmission rates, which we use to examine the potential impact of local pandemic conditions on dropout rates. The administrative features of our data allow us to measure dropout and attainment in three distinct ways: enrollment for the following academic year, graduation and presence for at least one exam during the academic year. These data collectively provide an unbiased measure of enrollment at the individual student level.

We focus in this paper on the French context, which offers a favorable institutional setting for investigating the relationship between dropout rates and exposure to the COVID-19 pandemic. First, the relatively low cost of university study allows us to closely examine how students react to the pandemic, as their decision-making is not strongly influenced by financial investments in tertiary education. Second, the government's response to the initial wave of the COVID-19 pandemic in France closely resembles that of other Western countries, particularly in terms of transitioning to online instruction for all students. Third, the French institutional context provides an opportunity to examine the causal impact of pandemic lockdown policies on student dropout, a feature that, to the best of our knowledge, has not been explored in the literature. Finally, in our investigation of the spatial distribution of student dropout, we employ a fine-grained geographical unit of analysis, which allows us to access detailed measurements of the unemployment rate and the severity of the pandemic.

Our initial findings provide compelling evidence that the first cohort affected by the COVID-19 pandemic was less likely to re-enroll for the subsequent academic year. Specifically, we observe a 3.7% decrease in the probability of re-enrollment of the COVID-19 cohort compared to the cohort from the previous year. The magnitude of the effect is higher compared to Failache, Katzkowicz, Parada, Querejeta, and Rosá (2024), as they find a decrease in enrollment behaviors of about 2% in Uruguay's main public university.¹ To put this decline into perspective in the French context, it is equivalent to the cumulative decline in re-enrollment observed in French higher education institutions over the preceding decade. We replicate this analysis to provide a more

¹ A companion article, Ye et al. (2022), documents dropout intentions among medical students in China, finding that the proportion of those intending to drop out declined from 13.7% to 6.8%. Our study extends this approach by examining actual dropout behaviors rather than just students' intentions and includes all students enrolled in French universities.

comprehensive understanding of enrollment patterns using alternative outcome measures: likelihood to graduate, and attendance at least one exam during the year. Our results indicate that students in the first cohort exposed to the COVID-19 were less likely to graduate. We do not find any overall effect on exam attendance, which indicates that our main results are not driven by absenteeism. Our results demonstrate that the decrease in dropout rates cannot solely be attributed to changes in grading practices or attendance at final exams.

Our second set of findings uncovers significant variations with student demographics and degree levels (undergraduate vs. graduate studies). Leveraging comprehensive individual enrollment data spanning the last decade, we conduct detailed pre-trends analysis on individual demographics, enabling us to document the relationship between these characteristics and enrollment behaviors during the pandemic. Specifically, we observe a higher likelihood of dropout among male compared to female students, non-free lunch students, and foreign students. Undergraduate students exhibit an increased probability of dropout, while we find no effect for Ph.D. students. Notably, first- and second-year undergraduate students were most affected by the pandemic, with their likelihood of re-enrollment decreasing by more 16.3% and 6.8%, respectively compared to the previous year. Furthermore, we investigate differences in enrollment behaviors at the field level in which we find a sharp decline on the likelihood to re-enrolled for students in Economics & Business, and Literature & arts. The observed heterogeneity in student demographics and fields suggests that the pandemic's unequal impact on enrollment behaviors could lead to lasting shifts in the composition of the student population in the coming years.

Moreover, we assess the medium-term impact of the pandemic on enrollment behaviors by replicating our analysis on the 2021 and 2022 cohorts. This approach allows us to investigate whether COVID-19 had an immediate effect on students or if its impact persists (or intensifies) over time. We first show that enrollment and graduation rates continue to decrease for the two cohorts exposed to the pandemic, indicating that the pandemic's effects are not limited to the short term. Specifically, we demonstrate that the decrease in enrollment rates is more pronounced among the second cohort exposed to the pandemic compared to the first. Next, we examine two sources of heterogeneity: (i) enrollment characteristics, and (ii) students' characteristics. We find that the lasting effect on the probability of dropping out is particularly pronounced among students with free lunch status, as well as first-, third-, and fifth-year students and those enrolled in PhD programs. Moreover, we show that the lasting effect of the pandemic on the probability of graduating varies based on free lunch status and socio-economic background, with this effect being particularly significant for both non-STEM students and undergraduates.

Finally, to gain a deeper understanding of the impact of policies aimed at containing the spread of the virus on university students, we leverage a natural experiment that occurred in France at the end of the first lockdown period. During this time, different regions in the western and eastern parts of the country were subjected to varying levels of policy stringency (e.g. restrictions on social gatherings and movement). Our institutional framework allows us to test the hypothesis that an increase in lockdown policies is negatively related to educational outcomes. Overall, we find that this institutional setting decreases enrollment behavior of about 3.8% for the students that have been exposed to stricter policies. To put this result into perspective, the impact of the additional policies implemented for one month is comparable in scale to the average effect of the COVID-19 pandemic itself.

We investigate two first mechanisms that may explain students' enrollment behaviors. Specifically, we examine the local severity of the pandemic and labor market opportunities for students. The first is based on the intuition that students who are either personally at higher risk of contracting the virus or who have relatives in a similar position may bear a significant mental burden due to the pandemic. We measure local exposure at a detailed geographical level by examining

excess mortality over the course of the pandemic, which avoids traditional measurement errors associated with variable testing capacity. The second line of investigation is based on the human capital investment approach, which looks at inter-temporal trade-offs between labor market costs and opportunities. The COVID-19 pandemic brought about significant changes in the labor market, which might have influenced students' tendency to enter the labor force rather than re-enrolling in university. We find little evidence that supports the idea that either mechanism explains students' decision to re-enroll. However, we find a sizable positive correlation between labor market opportunities and likelihood of graduating.

We then document the role of university quality and discuss several mechanisms and how they may intertwine with the COVID-19 pandemic. First, we consider three dimensions of university quality: (i) university effectiveness in keeping students on track, (ii) integration into the labor force, and (iii) salary after graduation. These versatile measures of university quality are based on the rationale that preventing dropout behaviors may not necessarily correlate solely with the ability to enhance labor market integration. Additionally, universities may have specific pedagogies that prevent dropout behaviors. The first measure, which uses a data-driven approach to assess dropout rates at the university level for the decade preceding COVID-19, bypasses the declarative nature of the second two measures. We do not find evidence supporting a consistent association between all measures of university quality and enrollment behaviors. This set of results suggests that enrollment behaviors are mainly driven by either individual or global factors. We then discuss several mechanisms that could explain why students dropped out of university, namely mental health, housing conditions, and digital availability at home.

This paper draws upon three distinct literatures to contribute to the ongoing examination of the impact of COVID-19 on educational outcomes. First, it examines the effects of school closures on learning outcomes, a topic that has been extensively studied across various countries, revealing significant learning losses (see [Betthäuser et al., 2023](#) for an extensive review of the literature). Underprivileged students, who have limited access to educational resources for remote learning, have disproportionately borne the brunt of the COVID-19 period ([Grewenig, Lergetporer, Werner, Woessmann, & Zierow, 2021](#); [Werner & Woessmann, 2023](#)). Second, the paper investigates the pandemic's impact on students' perceptions of returning to education and their subsequent choices. An increasing body of evidence suggests that the pandemic has influenced not only students' learning but also their decision-making regarding their educational paths ([Aalto, Müller, & Tilley, 2023](#); [Aucejo et al., 2020](#)). For instance, [Aalto et al. \(2023\)](#) find that the pandemic has decreased the likelihood of high school applicants in Sweden applying to top-ranked vocational programs. Given these findings, it is reasonable to anticipate that the pandemic may also have influenced university students' decisions to continue their enrollment in university. They may have faced increased financial stress in comparison to high school students and experienced disruptions in their educational journey.

The need to balance the pursuit of higher income through the acquisition of more human capital with the opportunity cost of forgoing participation in the labor market during a specific period introduces uncertainty regarding the impact of economic shocks on education ([Ferreira & Schady, 2009](#)).² According to a recent survey by [Wachter \(2020\)](#), university students' incomes after leaving education exhibit high sensitivity to economic fluctuations. College students leaving their studies without graduating during a recession earn 10% less on average over the ten years after leaving education. While many

² For example, [Bulman, Fairlie, Goodman, and Isen \(2021\)](#) demonstrate that income shocks induced by a lottery have a positive effect on school attendance, while ([Dang, Nguyen, Nguyen, & Phung, 2022](#)) show that these shocks affect expenditure on children's education.

studies have examined relationships between traditional demographic factors and university enrollment (Aina, Baici, Casalone, & Pastore, 2018; Gury, 2011; Montmarquette, Mahseredjian, & Houle, 2001), this paper specifically focuses on exploring the impact of these demographics on university dropout in times of ambiguity in both health and economic domains. In the context of the COVID-19 pandemic, students faced (i) significant financial constraints and (ii) the mental burden of both online learning and labor market downturns. Various studies highlight the negative impacts of the COVID-19 pandemic (Bulman & Fairlie, 2022; Schanzenbach & Turner, 2022), such as the decline in enrollment at U.S. community colleges by 11% and 9.5% between 2019 and 2020, respectively.³ This paper extends their findings to offer a comprehensive analysis focused on university students, particularly examining how lockdown policies' stringency influences their enrollment behaviors.

Third, the paper contributes to the literature documenting the impact of COVID-19 on inequalities. Stantcheva (2022) provides an overview of the impact of the pandemic on economic and social inequalities, examining four main dimensions of interest: inequalities across the income distribution, inequalities across sectors and regions, gender inequalities, and educational inequalities. Converging evidence shows that the pandemic and the associated economic policies have accentuated existing inequalities in most of these domains. In terms of education, studies show that school closures exacerbated pre-existing learning inequalities along dimensions such as wealth, urbanicity, gender, and children's ability to study from home (Agostinelli, Doepke, Sorrenti, & Zilibotti, 2022; Andrew et al., 2020; Parolin & Lee, 2021). Reducing inequalities among university students is crucial for addressing disparities in the labor market, especially among women and minorities who experience limited economic opportunities post-graduation and were disproportionately affected by the pandemic.

The rest of the document is organized as follows. Section 2 provides some institutional background on French higher education settings as well as information on the evolving policy response to COVID-19 in France during the study period. Section 3 describes the data and the construction of our main variables, along with some descriptive statistics on our main variables of interest. Section 4 presents our empirical approaches, detailing our identification strategies, their underlying assumptions, and how we test our hypotheses. Section 5 presents our results on the relationship between the effects of the COVID-19 pandemic and university dropout, and Section 6 concludes.

2. Institutional background

This section provides the French higher education system as well as the policy response to COVID-19 implemented during the 2020 academic year.

2.1. French higher education system

At the end of upper secondary school, French students take a national exam called the “*baccalauréat*”, and those who pass it are eligible to apply for tertiary education. The French higher education system includes three different types of post-secondary programs, two selective and one non-selective. While the “*Licence*” (undergraduate degree) at universities is mainly non-selective and is open to all high school graduates, other programs, such as two-year vocational programs (“*Sections de Techniciens Supérieurs*”), and “*Classes Préparatoire aux Grandes Ecoles*,” are selective.⁴ Because it is a largely non-selective

³ Looking at students before they enter tertiary education, Schueler and Miller (2023) find that pre-K-12 enrollment dropped by 4% between fall 2019 and fall of 2020.

⁴ *Classes Préparatoire aux Grandes Ecoles* are among the most prestigious and selective post-secondary programs. Their focus is on preparing students to take the entry exams for the most competitive higher education institutions, the “*Grandes Ecoles*”.

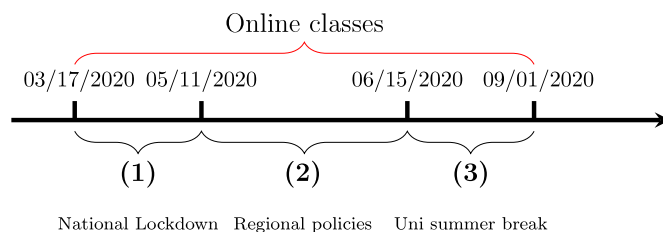


Fig. 1. Timeline of the policy response to the COVID-19 pandemic.

sector, we focus on students enrolled in a university degree program. University is the most popular higher education track for secondary students in France, with 60% of those who obtain their “*baccalauréat*” opting to enter university⁵

Two main features make the higher education system in France a particularly suitable institutional context for investigating the possible exacerbation of educational inequalities by the COVID-19 pandemic. First, the overwhelming majority (84%) of students are enrolled in tuition-free public institutions, where the average annual fee for enrollment as an undergraduate at a public university was 170 euros as of 2022 (CampusFrance, 2022). In contrast to the situation in the U.S., where higher education costs can significantly influence students' decision-making, the relatively low cost of studying at a university in France allows us to closely examine how students respond to the pandemic without this added financial burden. Second, although public universities in France are mainly tuition-free (Moulin, Flacher, & Harari-Kermadec, 2016), individuals' access to prestigious academic programs is heavily influenced by their social and economic background (Benveniste, 2021; Bonneau, Charrouset, Grenet, & Thebault, 2021; Bonneau & Grobon, 2022).⁶

2.2. French policy response to the COVID-19 in terms of education

The COVID-19 pandemic compelled governments around the world to implement stringent measures to curb the transmission of the virus. The closure of schools and universities is among the most severe policies enacted in this period. A majority of Western countries implemented it in the initial phase of the pandemic, France included. Fig. 1 illustrates the timeline of policy responses in France. On March 17th, President Emmanuel Macron declared a nationwide lockdown, initially for a duration of two weeks, which was subsequently extended to eight weeks until May 11th. Following this, from May 11th to June 15th, the government adopted a regional approach, selectively relaxing lockdown measures based on the local prevalence of the virus. Consequently, varying levels of policy stringency were observed between eastern France and the rest of the country. In Section 4.2, we explore these regional disparities in greater detail.

National political guidelines played a crucial role in determining the opening and closure of universities during the COVID-19 pandemic. Specifically, regardless of their level of exposure to the virus, all universities were mandated to close from May 11th until the summer break. This uniform national policy ensured a standardized teaching format for all tertiary education students during the 2020 academic year, allowing the effects of COVID-19 policies to be comprehensively evaluated. It

⁵ https://publication.enseignementsup-recherche.gouv.fr/eesr/FR/T943/1_acces_a_l_enseignement_superieur/

⁶ More specifically, Bonneau and Grobon (2022) shows that on average, a 10 percentile rank increase in parental income distribution is associated with a 5.8 percentage point rise in the proportion of children accessing higher education. This effect is stronger for children in the top half of the income distribution. Interestingly, they find that the overall level of inequality in this context is similar to that observed in the United States.

is important to note, however, that the quality of teaching may vary depending on the technical skills of instructors and their effectiveness in a distance education situation (Dincher & Wagner, 2021).

3. Data, measures and descriptive statistics

We seek to investigate the influence of COVID-19 and the associated policy and economic conditions on university students' dropout rates by analyzing comprehensive enrollment data. To do so, we require data capturing variations in COVID-19 exposure both across different academic years and within specific cohorts. In Section 3.1, we present the main measures used in the paper, based on records of all students' enrollment in public universities in France. Appendix A presents the comprehensive sources of information used in this paper. By integrating multiple administrative data sources, our analysis aims to determine whether the pandemic and its localized impacts directly affected university dropout rates. Section 3.2 presents the descriptive statistics for the cohort preceding the COVID-19 pandemic and the cohort affected by the pandemic.

3.1. Data and measures

We use a comprehensive dataset on university enrollment to obtain our primary information. The dataset we employ is derived from the "Système d'Information sur le Suivi de l'Étudiant" (student information system, or SISE), which is managed by the Statistical Office of the French Ministry of Higher Education. This dataset provides us with individual administrative data on the enrollment status of all students from 2012 to 2022. We consider the cohorts' re-enrollment rate for the following academic year. For instance, the year 2019 corresponds to the re-enrollment rate of students from the 2019 academic year for the subsequent 2020 academic year. Moreover, to avoid duplication, in cases where students were concurrently enrolled in multiple degrees, we consider only the main degree in the administrative french system per student per year.⁷

Our analysis relies on observable indicators of student dropout, which are derived from the university's enrollment register. The primary measure of interest is a binary variable indicating whether a student remains enrolled at the university in the subsequent academic year. We also examine whether students successfully obtain their degree in the expected graduation year (e.g. third year of university studies for a bachelor's degree, and fifth year of university studies for a master's degree). We also use a binary indicator of students' attendance for at least one final exam. These measures are exclusively drawn from the administrative register, ensuring their objectivity and lack of bias. However, it is important to note that once students discontinue their enrollment, we lack precise information on their subsequent trajectories, such as their entry into the labor market or their choice to live with their parents.

There are several limitations associated with our measure of school dropout, which we briefly address here. First, we are unable to track potential changes in the grading system or exam difficulty, which could influence the passing rate. It is likely that universities, heavily impacted by the pandemic, implemented more lenient exams. To mitigate this limitation, we rely on enrollment decisions in the subsequent year rather than exam scores. Additionally, it is increasingly common for students to participate in international programs such as Erasmus. Travel restrictions during the COVID-19 pandemic had a major impact on student mobility, which could lead to a bias in our analysis. Namely, it introduces an attenuation bias, as international students usually less likely to re-enroll are more likely to choose a France-based university

⁷ After identifying primary enrollments, we exclude duplicates (0.13%) and individuals with incomplete demographics (24%), resulting in 15,600,845 enrollment choices from 7,785,743 students.

Table 1
Pre-COVID and COVID period cohort composition.

	Treated COVID-19 cohort	Baseline 2019	Difference
Demographics			
Female	0.569	0.587	-0.019***
Non-French students	0.141	0.130	0.010***
Free Lunch Status	0.311	0.215	0.097***
Low SES	0.256	0.233	0.022***
Middle Low SES	0.210	0.221	-0.011***
Middle High SES	0.186	0.202	-0.016***
High SES	0.348	0.344	0.004***

Notes: Each row presents the average value for students enrolled in university in the 2019 and 2020 academic years for the variables listed on the left. Column (1) represents the cohort exposed to COVID-19, and column (2) represents the 2019 cohort. Column (3) gives the results of a two-tailed t-test on the difference in means, with asterisks indicating traditional levels of statistical significance (***, **, * for 0.01, 0.05, 0.1, respectively).

during the pandemic ; and, conversely, foreign students studying in France probably found it more difficult to return to France after the pandemic. To address this issue, we perform an analysis excluding observations of foreign students who are not enrolled in an exchange year (see Table B.1 in Appendix B.1).

3.2. Descriptive statistics

Table 1 presents the average demographic characteristics of students enrolled in university in 2019, and compares them to those of students enrolled in university in the first year of the COVID-19 pandemic. In the 2019 cohort, students mostly come from a high socio-economic background (34.4%). Female are slightly over-represented as they account for 58.7% of the students' population. The non-french and free lunch status represent a non-negligible share by consisting in 13% and 21.5% respectively. Turning to the COVID-19 cohort, we do not find striking differences as women and high SES status are over-represented (56.9%, 34.8% respectively). We do observe a slight increase in the proportion of free lunch status and low SES students and a small decrease in the share of female in the cohort exposed to the pandemic. The magnitude remains however small. These descriptive statistics show that the difference between cohorts is small (albeit statistically significant, due to the large sample size), ruling out a possible bias in our analysis due to changes in the distribution of student characteristics.

4. Empirical approach

Section 4.1 presents our main empirical approach. Section 4.2 describes the quasi-natural experiment in differential policy stringency during the first wave of COVID-19.

4.1. Exposure to COVID-19 and drop-out

We first estimate the probability of being enrolled in a university for the following year using a logit model. Our dependent variable, y_{ijt} , is a dummy variable equals to 1 if the individual i enrolled at the university j in $t - 1$ re-enrolls in year t , and equal to 0 if individual i is enrolled in year $t - 1$ but does not re-enroll in year t . We estimate the following specification:

$$y_{ijt} = \alpha + \sum_{\substack{t=2013 \\ t \neq 2019}}^{2020} \beta_t \text{year}_t + \mathbf{X}'_i \delta + \Theta_j + \epsilon_{it} \tag{1}$$

The primary focus of this study is the variable of interest, year_t , with $t = 2020$. This variable measures the probability of re-enrollment for the subsequent academic year in 2020 relative to 2019. The vector

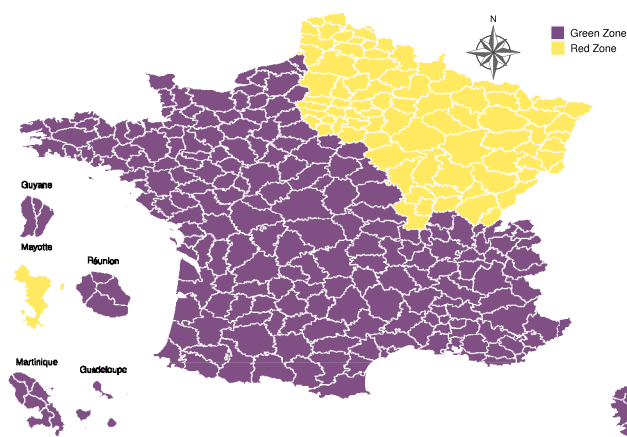


Fig. 2. Regional lockdown policies.

X'_i comprises individual-level controls (gender, free lunch status, SES, nationality), θ_j represents university fixed effects, and ϵ_{it} is the error term clustered at the university level. To analyze the heterogeneity of our effects, (i) we consider the effect for each year of study, and (ii) we follow previous studies in constructing an aggregate measure of area of study with three values: humanities, soft-STEM (biology, medicine), and hard-STEM (see Charoussat & Monnet, 2022).

To achieve an unbiased assessment of the impact of the COVID-19 pandemic, enrollment behavior changes should be solely attributed to a change in β_t . The underlying assumption of this approach is that we do not detect a systematic difference in the pre-trend, as typically observed in an event-study design. As discussed further in Section 5.1, there is a continuous decrease in the likelihood of enrollment for the subsequent academic year, posing a direct challenge to our identification strategy. While one might suggest forecasting the enrollment rate for the COVID-19 pandemic based on previous years, we argue that such a methodological choice would introduce hypotheses that could render the results less reliable compared to a more straightforward approach. This initial approach cannot yield estimates of the causal impact of the pandemic on enrollment behaviors, but rather provides insight into the magnitude of the observed decrease for cohorts experiencing the pandemic.

4.2. Policies stringency and university drop-out: Quasi-experimental evidence

Our first approach allowed us to quantify the overall change in re-enrollment behaviors among university students without regard to differences in the policies implemented to contain the spread of the virus. We now take advantage of a quasi-natural experiment in France to test the hypothesis that lockdown regimes of differing stringency will differentially impact enrollment rates. The French government created a quasi-natural experiment by classifying areas as either “red” or “green” based on the number of recorded COVID-19 cases at the end of the first lockdown. This quasi-experimental setup offers a unique opportunity to compare dropout behaviors between two regions of France that share similar characteristics but experienced different policies. Fig. 2 presents the spatial distribution of both areas over the French territory. Specifically, a significant number of gathering places (restaurants, cinemas, beaches, large shopping centers, parks and gardens) and educational establishments (nursery and secondary schools) were closed for several weeks following the initial lockdown. Importantly, the decision to implement these policies was not based on educational outcomes, as the primary criterion for implementing additional policies was the prevalence of the virus at the end of the initial lockdown.

The timing and intensity of the variation in university closures may initially appear limited, as the first lockdown was more stringent, and the timing of this natural experiment may constrain the observed effects since most teaching activities were already completed. One might argue that the short duration of the period during which regional heterogeneity in university closures was in place does not allow for extensive exploration. However, the timing of this natural experiment is crucial in influencing students’ enrollment behaviors, particularly because it coincides with take-up exams and the early phase of administrative enrollment for the following academic year. Even a limited change in their educational environment during this period is likely to influence students’ attitudes toward their educational pathway.

To estimate the causal impact of lockdown on dropout behaviors, we assign the green zone as the control group and the red zone as the treated group. Our hypothesis is that, in the absence of COVID-19 and associated public policies, the dropout trends between both zones would have been similar on average. This institutional framework includes both direct and indirect factors that could influence students’ decisions to drop out. First, there is a direct effect of the pandemic, as students residing in a red zone are subject to the direct impacts of higher numbers of (recorded) cases. Second, there is the potential indirect effect of the implementation of stricter lockdown policies in response to increased numbers of cases, which is of particular interest to us here. Through an examination of this quasi-natural experimental situation, we can refine our previous analysis by providing causal evidence of the impact of different levels of policy stringency on student dropout.

Formally, using a difference-in-differences approach, we estimate the following equation:

$$y_{ij} = \alpha + \beta \text{COVID}_i + \delta \text{Red}_i + \rho \text{COVID}_i \times \text{Red}_i + X'_i \delta + \theta_j + \epsilon_i \quad (2)$$

The coefficient of interest, ρ , measures the difference between the red and green conditions for individuals in the COVID-19 cohort. The dependent variable is a binary variable, equal to 1 if the individual is observed in the set of individuals enrolled for the subsequent academic year. We introduce the dummy variable, Red_i , a dummy variable indicating whether the urban area of individual i belongs to the red zone, which thus takes a value of 1 if the observation is in the treated group. X'_i represents a vector of individual controls, θ_j represents university fixed effects and ϵ_i is the error term clustered at the university level.

The validity of our estimation strategy relies on the parallel trend assumption, i.e. the assumption that there is no difference in trends in dropout between the two areas outside the treatment period. We provide evidence supporting this assumption in Section 5.5. We acknowledge that this dual distinction between green and red zones does not allow us to depict the potential impacts very precisely as we are only able to compare *in average* the differences between both zones. Following Brandily, Brébion, Briole, and Khoury (2021), who used the same natural experiment, they found similar pre-trends in mortality for both zones, although the red zone had a higher proportion of municipalities in the poorest quartile. Therefore, while the treatment was not conditioned on educational outcomes, we cannot claim perfect exogeneity.

5. COVID-19 and university enrollment

5.1. The impact of COVID-19 on student drop-out

Fig. 3 presents the overall trends for our three key variables: enrollment, exam attendance, and degree attainment. The figure shows that each year, approximately 70% of the total population tends to re-enroll for the following year, approximately 90% attend the exams, and

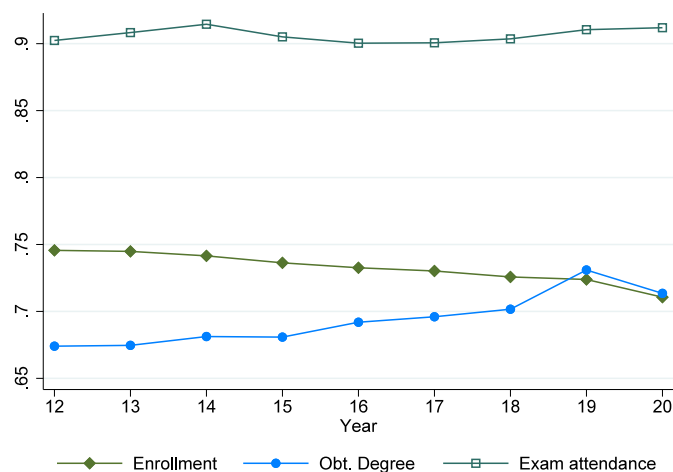


Fig. 3. Enrollment behaviors between 2012 and 2020.

Notes: The figure presents the yearly averages of our educational outcomes. Each dot represents the average value of the respective outcome for the corresponding calendar year. Enrollment is defined as 1 when an individual is observed in the subsequent academic year. The variable exam attendance takes a value of 1 if the individual attends at least one final exam, while graduation indicates whether the individual successfully obtained their degree at the end of a graduating academic year.

around 70% of those in what would normally be the final year of their program successfully obtain their degree.⁸

Fig. 3 presents a detailed analysis of changes in educational outcomes during the pandemic. Students observed during the 2021 academic year had a 1.32 percentage point lower likelihood of re-enrollment compared to the previous year (two-tailed t-test, $t = 34.309$, $p < 0.000$). In other words, the decrease observed in the first academic year following the start of the pandemic is roughly equivalent in size to the cumulative decline in re-enrollment over the preceding 10-year period. Interestingly, however, we find only a 0.14% increase in the probability of exam attendance (two-tailed t-test, $t = 16.482$, $p < 0.001$), and a 1.74 percentage point decrease in graduation rate (two-tailed t-test, $t = 6.457$, $p < 0.000$). These last finding may be attributed to the notion that online exams increased exam attendance.

Table 2 presents a formalization of the initial findings derived by estimating Eq. (1) for different subgroups. Column (1) of panel A provides an estimate using the overall sample, and the following columns provide estimates first by area of study and then by level of degree program (i.e. undergraduate, master's, PhD). The columns in panel B give estimates derived from separate analyses for each year level in the Bologna system to account for the potential influence of the expected time lapse between completing a year of study and entering the labor force. This factor can significantly impact an individual's ability to dedicate themselves to their studies, particularly during a pandemic. We take advantage of the extensive time-span available in enrollment behaviors to analyze pre-trends for the dependent variables of interest over demographics in Appendix B.2. We observe pre-trends similar to those among the overall population in enrollment and, to some extent, in graduation rates (see Fig. B.1).⁹

Panel A in Table 2 reveals that overall, students' probability of re-enrollment for the 2021 academic year dropped by 3.7% compared to the previous academic year, controlling for basic demographic characteristics. Further disaggregation of the analysis by area of study

⁸ Note that in the dataset, the variable obtaining a degree is coded as missing if the academic year is not a graduating year.

⁹ However, analyzing pre-trends for exam attendance proves less straightforward, as we do not observe consistent patterns over time among subgroups. Therefore, distinguishing between underlying statistical noise and variation associated with the COVID-19 pandemic is challenging.

indicates that students in hard-STEM experienced a decrease in the probability of re-enrollment of about 5.6%. We refine this distinction by field by having a more diverse definition of disciplines.¹⁰ We estimate Eq. (1) for each field under scrutiny in Appendix B.3. We observe a significant decline in the likelihood of re-enrollment for students in Economics & Business, and Literature & Arts (see Fig. B.2). However, we lack a clear explanation for these findings, given the substantial between-field heterogeneity in student populations and pedagogical approaches, and the fact that the pre-trend assumption is not fully satisfied for the period analyzed. Columns (5) to (7) in Table 2 show that it was undergraduate students specifically who were more likely to drop out during the pandemic (by 9.4%). Interestingly, graduate students are 4.6% more likely to re-enroll for the following academic year. This contrast between undergraduate and graduate students suggests that the pandemic encouraged continued studies for the latter, while discouraging enrollment for new students.

Panel B of Table 2 reveals significant heterogeneity with movement through degree programs, as the estimated coefficient varies for almost every individual year considered independently. Students in their first and second year after entering university were the most likely to drop out ($\beta = 0.837$ and $\beta = 0.932$, respectively). Students in their fourth year are more likely to enroll for the following academic year ($\beta = 1.182$). First- and second-year undergraduate students, who have recently entered university, may have been discouraged by the pandemic, decreasing their motivation to continue their studies.

The final result in this line is consistent with previous findings indicating that enrollments and retention at 2-year/community colleges were significantly affected by the pandemic (Bulman & Fairlie, 2022; Schanzenbach & Turner, 2022). However, this impact has often been attributed to differences in student characteristics at these institutions, such as lower income or weaker academic backgrounds. Our analysis reveals that students enrolled in these programs do not exhibit significantly different demographics compared to their peers (see Table B.2 in Appendix B.4), suggesting that enrollment disparities cannot solely be explained by these factors. Instead, our results indicate that this heterogeneity may be driven by variations in expectations or study habits, although direct testing for this remains challenging.

5.2. Alternative measures of enrollment

Table 3 replicates panel A of Table 2 for alternative measures of dropout: probability of graduation (for students in a graduation year) and attendance at one or more final exams. The inclusion of these measures serves two purposes. First, it addresses the measurement error resulting from teachers implementing less difficult exams in the year of the COVID-19 pandemic, which increases the likelihood of students being observed for the following year. This inherent bias would tend to decrease the estimated impact of the pandemic on re-enrollment, as making students more likely to pass their exams would also make them more likely to enroll for the following academic year. Furthermore, extensive evidence demonstrates the existence of a grading bias during the pandemic (Chan, 2022), which logically translates into a higher likelihood of graduation. Second, it considers pre-existing characteristics associated with dropout that go beyond academic performance alone. For example, non-attendance at final exams may serve as an initial step towards university dropout, which our previous measures may not fully capture. Moreover, such behavior is expected to have been more pronounced during the pandemic, given the increased rates of

¹⁰ We consider the following field based on the french administration: Law - Political Science ; Economics & Business ; Social administration ; Literature & arts ; Languages ; Humanities ; Biology ; Sports ; Medicine ; Odontology ; Pharmacy ; Hard STEM ; Multidisciplinary law & economics ; Multidisciplinary humanities ; Multidisciplinary sciences ; Multidisciplinary health ; Pluridisciplinary.

Table 2
Impact of COVID-19 on student dropout.

Panel A. Re-enrollment by Area of Study & Degree Level							
	Overall (1)	Non-STEM (2)	Soft-STEM (3)	Hard-STEM (4)	UG (5)	G (6)	Ph.D. (7)
2020	0.963*** (0.010)	0.980* (0.010)	0.955* (0.027)	0.944*** (0.016)	0.906*** (0.010)	1.046** (0.019)	0.984 (0.040)
Observations	12,510,282	7,286,615	2,256,941	2,966,165	7,685,680	4,401,395	423,171
Log Likelihood	-7,001,286	-4,230,530	-1,032,694	-1,665,664	-4,062,774	-2,628,237	-239,164.02

Panel B. Re-Enrollment by Year of University Study							
	Overall (1)	First year (2)	Second year (3)	Third year (4)	Fourth year (5)	Fifth year (6)	Sixth year (7)
2020	0.963*** (0.010)	0.837*** (0.012)	0.932*** (0.019)	1.041 (0.027)	1.182*** (0.031)	0.985 (0.023)	0.987 (0.026)
Observations	12,510,282	3,821,188	2,189,929	2,198,196	1,644,896	1,641,031	1,014,426
Log Likelihood	-7,001,286	-1,865,381	-923,076.72	-1,290,878	-683,536.41	-1,068,656	-540,191.05

Notes: This table reports estimates of the probability of re-enrollment for the following year after the academic year 2020 relative to 2019. Year numbering is expressed as the odd-ratio with the 2019 as a reference. The sample includes all students enrolled in a university degree in France from 2012 to 2020. Each column presents a logit regression performed separately on the corresponding sample. The regression includes university fixed effects (to account for differences in university quality) and the student characteristics listed in Table 1. Standard errors (shown in parentheses) are adjusted for clustering at the university level. Asterisks indicate traditional levels of statistical significance (***, **, *, for 0.01, 0.05, 0.1, respectively).

Table 3
Alternative measures of drop-out.

Panel A. Graduation by Area of Study & Degree Level						
	Overall (1)	Non-STEM (2)	Soft-STEM (3)	Hard-STEM (4)	UG (5)	G (6)
2020	0.926*** (0.016)	0.910*** (0.024)	0.953 (0.061)	0.855*** (0.026)	0.861*** (0.020)	1.014 (0.023)
Observations	3,716,148	2,314,034	474,079	927,987	2,141,674	1,573,321
Log Likelihood	-2,219,261	-1,235,760	-278,771.64	-529,759.67	-1,247,990	-925,110.03

Panel B. Attendance at least at 1 Final Exam by Area of Study & Degree Level						
	Overall (1)	Non-STEM (2)	Soft-STEM (3)	Hard-STEM (4)	UG (5)	G (6)
2020	1.057 (0.045)	1.108*** (0.025)	1.046 (0.212)	0.985 (0.055)	1.197*** (0.078)	1.149*** (0.049)
Observations	10,461,022	6,436,884	1,418,238	2,605,299	1,987,933	1,397,519
Log Likelihood	-3,097,718	-1,919,645	-288,679.45	-831,452.11	-416,049.41	-364,499.83

Notes: This table reports estimates of the relative probability of graduation and exam attendance in 2020 relative to 2019. The sample for panel B consists of all students enrolled in a graduation year in France from 2012 to 2020, while the sample for panel A covers all students enrolled in any degree program at a public university. Each column presents a logit regression performed separately on the corresponding sample. The regression includes university fixed effects (to account for differences in university quality) and the student characteristics listed in Table 1. Standard errors (shown in parentheses) are adjusted for clustering at the university level. Asterisks indicate traditional levels of statistical significance (***, **, *, for 0.01, 0.05, 0.1, respectively).

student absenteeism and lack of motivation to study already extensively highlighted by practitioners and researchers (Chen et al., 2022).

Panel A of Table 3 presents the overall impact of the pandemic on students' likelihood of graduating. Interestingly, the results indicate that, on average, the cohort that was first exposed to the pandemic was 7.4% less likely to graduate than the previous cohort. This finding may be seen as somewhat surprising, as many university instructors adjusted the difficulty of their exams to accommodate the extraordinary circumstances of the pandemic (Chan, 2022), which in principle should increase students' likelihood of graduating. The results by area of study reveal noteworthy variations. Specifically, degree completion rates were lowest among students enrolled in hard-STEM programs ($\beta = 0.855$), followed by non-STEM students ($\beta = 0.910$). No decrease in graduation rate is observed for students in soft-STEM programs. Furthermore, we found that undergraduate students overall were 3.9% less likely to obtain their degrees in the pandemic year, while we did not observe a significant impact of the pandemic on graduate students' likelihood of graduating. This difference could potentially be attributed

to the fact an expectation among final-year graduate students of being able to enter the labor force upon graduation, stimulating them to make the effort to graduate in time.

Panel B of Table 3 reveals a contrasting finding: a lack of significant change in attendance at final exams in the pandemic year compared to the previous year—apart from increases in attendance at exams in the non-STEM, undergraduate and graduate sub-samples (of 10.8%, 19.7% and 14.9% respectively). These results can be explained by the definition of our main variable, which defines final exam attendance as showing up for at least one exam. Since the majority of exams were conducted online, students were unlikely to completely miss all of them. However, not all areas of study and degree levels examined in panel B exhibit significant effects.

5.3. Heterogeneity of the impact of COVID-19 on student drop-out

Here, we expand on our previous analysis by investigating heterogeneity in dropout behaviors during the pandemic based on individual

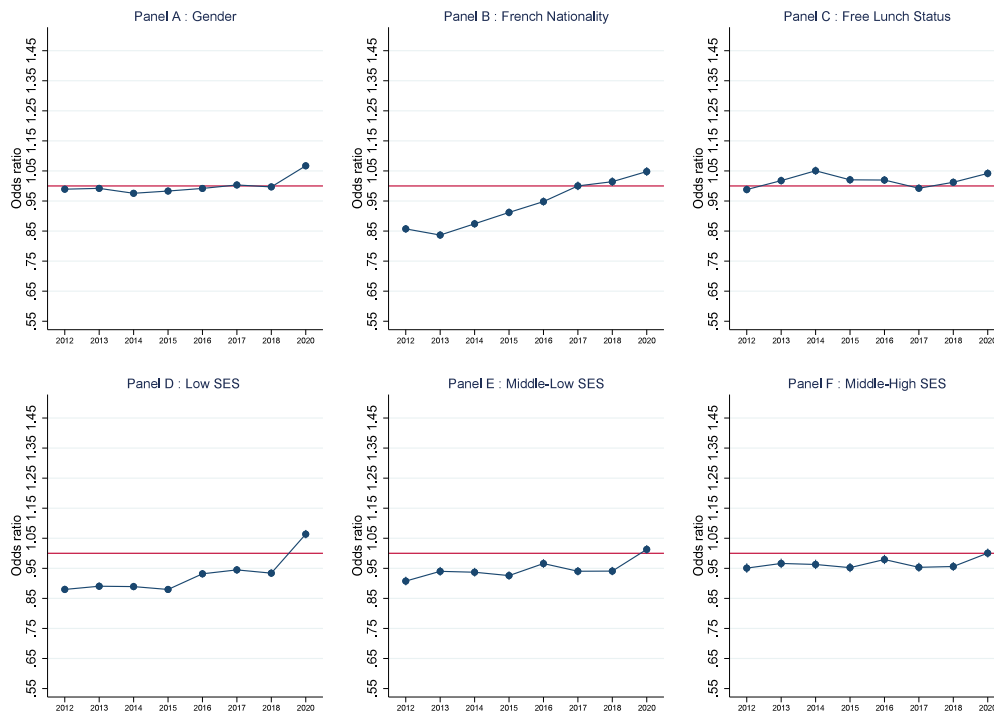


Fig. 4. Demographics and likelihood to drop-out.

Notes: The figure presents the heterogeneity analysis based on a logit model (Eq. (3)). We cluster standard errors at the university level. The dependent variable in focus is the probability of re-enrollment for the ensuing academic year. The coefficient shown in the graph represents the odds ratio for the interaction term between the demographic category and the year. The reference year is the one preceding the pandemic. An odds ratio that overlaps with the red horizontal line indicates a significant change in the likelihood of dropping out for members of the corresponding demographic during the pandemic. We calculate the equation for each demographics under scrutiny, and create a separate chart for each estimate to show the relevant parameter clearly. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

characteristics. Specifically, we consider four key characteristics: gender, socioeconomic status, nationality (French or foreign), and free lunch status. We estimate the following specification to quantify the marginal effect of these specific characteristics relative to the previous years.

$$y_{ijt} = \alpha + \sum_{t=2013}^{2020} \beta_t \text{year}_t + \delta X_i + \sum_{t=2013}^{2020} \gamma_t \text{year}_t \times X_i + \mathbf{X}'_i + \Theta_j + \epsilon_{it} \quad (3)$$

The parameter of interest, γ_t , represents the coefficient for the characteristics X of individual i in year t . We can test for pre-trends in a manner similar to an event study design by estimating the relative difference between 2020 and the previous years for each set of individual characteristics. Specifically, each demographic is compared to a reference group (e.g. comparing women to men), with the resulting coefficient interpreted as the first difference for each characteristic. On this basis, it can be argued, in the absence of pre-trends, that the COVID-19 pandemic led to differential dropout behaviors depending on individual characteristics. It should be noted, however, that this empirical approach does not allow us to analyze whether the pandemic creates new inequalities based on demographics, but only if it exacerbates pre-existing ones. We present the estimates of Eq. (3) in Fig. 4. The figure is divided into six panels, each representing a different demographic group. The top panel presents results for three demographic characteristics: gender, nationality, and free lunch status. The bottom panel shows the heterogeneity analysis for three different socioeconomic status groups, with high SES as reference. The coefficients are expressed relative to a reference academic year, 2019, and the red line indicates an odds ratio of 1.

Fig. 4 presents three significant sources of heterogeneity that exhibit statistical differences from their pre-trends. Specifically, our findings indicate that students with free lunch status, french nationality and

women were more likely to re-enroll compared to the previous year. The higher likelihood of re-enrollment among women might be attributable to stronger study habits or a greater ability to make inter-temporal trade-offs, which enabled them to stay on track during the pandemic. Our results also indicate that French students were more likely to re-enroll compared to international students. This is likely explained by the severe restrictions on international student mobility, notably due to travel restrictions, associated with the pandemic.

We also replicate this analysis with our alternative measures of enrollment, likelihood of graduating and attendance at final exams. The results are presented in Appendix B.5. Fig. B.3 presents the heterogeneity analysis on the likelihood of graduating. Consistent with our results on enrollment behaviors, we observe that women are less more likely to graduate. On the other hand, we do not find compelling evidence that other demographics are associated with the graduation rate. Fig. B.4, on the other hand, shows significant heterogeneity in the likelihood of attending at least one exam. Specifically, we find that male students were significantly less likely to attend at least one final exam.

5.4. Lasting effect of the pandemic on students' enrollment behaviors

Did the pandemic disrupt higher education? On one hand, the pandemic may have discouraged students from pursuing higher education, as their experience with online learning might have prompted them to enter the labor force instead. On the other hand, it is also plausible that students paused their studies to avoid the mental burden associated with inadequate teaching facilities. We address this question by examining students' enrollment behaviors in the years following the COVID-19 pandemic (2021 and 2022). We analyze the magnitude of the effect after controlling for individual and university characteristics by replicating our analysis from Section 5.1 in Table 4. Specifically, we estimate Eq. (1) and present the odds ratios for the 2020, 2021, and

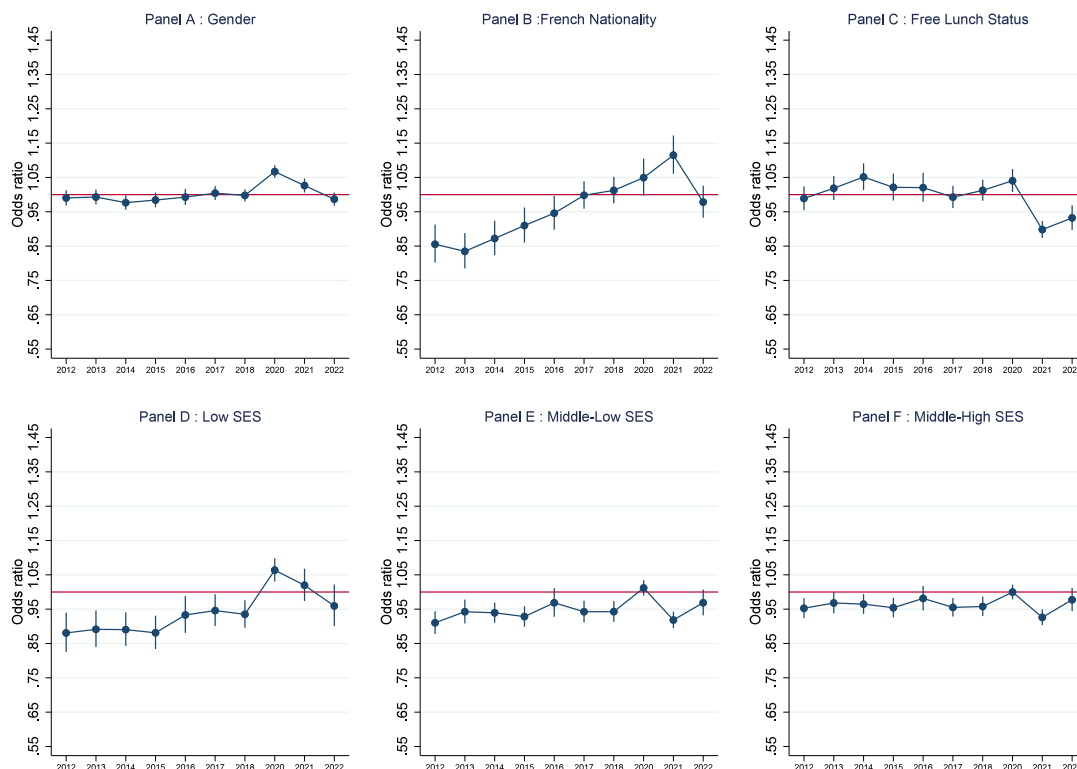


Fig. 5. Lasting effect of the pandemic based on students' demographic.

Notes: The figure presents the heterogeneity analysis based on a logit model (Eq. (3)). We cluster standard errors at the university level. The dependent variable in focus is the probability of re-enrollment for the ensuing academic year. The coefficient shown in the graph represents the odds ratio for the interaction term between the demographic category and the year. The reference year is the one preceding the pandemic. An odds ratio that overlaps with the red horizontal line indicates a significant change in the likelihood of dropping out for members of the corresponding demographic during the pandemic. We calculate the equation for each demographics under scrutiny, and create a separate chart for each estimate to show the relevant parameter clearly. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2022 cohorts relative to the 2019 cohort.¹¹ This approach allows us to compare changes in magnitude or the consistency of the coefficients across cohorts based on specific enrollment characteristics (e.g., fields of study, year of enrollment).

We find that the coefficients suggest that, on average, dropout rates are higher compared to the pre-COVID levels ($\beta_{2020} = 0.962$, $\beta_{2021} = 0.793$, $\beta_{2022} = 0.777$). The breakdown by field of study indicates that students in both soft-STEM ($\beta_{2022} = 0.738$), non-STEM ($\beta_{2022} = 0.764$), and hard-STEM ($\beta_{2022} = 0.822$) fields are affected by COVID-19 in the long run. Although Ph.D. students appeared to be spared during the first year of the COVID-19 pandemic — likely because, unlike other students, they do not have to take exams every year and their dropout may therefore be less immediate — in the following years they faced significant dropout rates ($\beta_{2021} = 0.934$, $\beta_{2022} = 0.763$). More specifically, the three cohorts post-COVID-19 display the same pattern, where first-year university students have a high likelihood of dropping out ($\beta_{2020} = 0.839$, $\beta_{2021} = 0.710$, $\beta_{2022} = 0.685$).

An intriguing pattern emerges among students at the end of graduation years. We find a continuous decline of significant magnitude in re-enrollment rates for students in their third and fifth years of study, while these populations did not drop out during the first year of the pandemic. Specifically, in 2022, we observe that third- and fifth-year students are 25.4% and 29.8% less likely to enroll for the

following academic year, respectively. Overall, our findings indicate that the COVID-19 pandemic led to a medium-term shift in enrollment behaviors, and that populations initially spared from the effects of the pandemic (students in soft-STEM fields, those in graduation years such as the third and fifth years of study, and those in PhD programs) eventually experienced negative effects on their likelihood of re-enrolling in university.

Panel C in Table 4 presents the coefficients for the years 2020 and 2021, showing the impact of the COVID-19 pandemic on graduation rates across various fields of study and education levels. Column (1) indicates that the overall graduation rate decreased significantly in both 2020 ($\beta_{2020} = 0.926$) and 2021 ($\beta_{2021} = 0.794$). When disaggregating by field of study, we observe that Non-STEM fields (Column 2) experienced a significant decrease in graduation rates in both years, with the effect being more pronounced in 2021 ($\beta_{2021} = 0.675$). Interestingly, Soft-STEM fields (Column 3) do not exhibit statistically significant changes. In contrast, Hard-STEM fields (Column 4) show significant reductions in graduation rates in both 2020 ($\beta_{2020} = 0.856$) and 2021 ($\beta_{2021} = 0.852$), highlighting a consistent impact of the pandemic on these students. The breakdown by education level reveals that undergraduate students (UG) in Column (5) faced a substantial decline in graduation rates, particularly in 2021 ($\beta_{2021} = 0.680$), while graduate students (G) in Column (6) did not show statistically significant changes in either year.

We replicate our former heterogeneity analysis based on students' demographics. Each plot in Fig. 5 should be interpreted following a similar methodology as in Section 5.3, observing stable pre-trends before the pandemic for each demographic under scrutiny. The lasting

¹¹ Unfortunately, the data on graduation rates is not available for the last cohort at the time of the study.

Table 4
COVID-19 on student dropout: 2012 to 2022.

Panel A. Re-enrollment by Area of Study & Degree Level							
	(1) Overall	(2) Non-Stem	(3) Soft-STEM	(4) Hard-STEM	(5) UG	(6) G	(7) Ph.D.
2020	0.962*** (0.009)	0.979** (0.010)	0.956 (0.026)	0.944*** (0.016)	0.906*** (0.010)	1.044** (0.019)	0.987 (0.040)
2021	0.793*** (0.008)	0.771*** (0.008)	0.827*** (0.030)	0.823*** (0.014)	0.745*** (0.010)	0.862*** (0.015)	0.934* (0.039)
2022	0.777*** (0.010)	0.764*** (0.010)	0.738*** (0.031)	0.822*** (0.017)	0.764*** (0.011)	0.793*** (0.020)	0.763*** (0.043)
Observations	15,600,845	8,983,672	2,867,710	3,748,453	9,623,039	5,467,243	510,501
Log Likelihood	-8,880,372	-5,293,874	-1,368,283	-2,128,543	-5,205,066	-3,295,734	-291,275.2

Panel B. Re-Enrollment by Year of University Study							
	(1) Overall	(2) First year	(3) Second year	(4) Third year	(5) Fourth year	(6) Fifth year	(7) Sixth year
2020	0.962*** (0.009)	0.839*** (0.012)	0.932*** (0.018)	1.039 (0.027)	1.182*** (0.030)	0.987 (0.023)	0.986 (0.027)
2021	0.793*** (0.008)	0.710*** (0.010)	0.697*** (0.015)	0.844*** (0.022)	0.920*** (0.026)	0.793*** (0.015)	0.844*** (0.032)
2022	0.777*** (0.010)	0.685*** (0.012)	0.965 (0.041)	0.746*** (0.019)	0.888*** (0.032)	0.702*** (0.015)	0.669*** (0.032)
Observations	15,600,845	4,727,807	2,792,847	2,779,920	2,013,889	2,040,557	1,245,253
Log Likelihood	-8,880,372	-2,360,152	-1,204,804	-1,656,559	-828,503.48	-1,309,379	-675,013.88

Panel C. Graduation Rate						
	(1) Overall	(2) Non-Stem	(3) Soft-STEM	(4) Hard-STEM	(5) UG	(6) G
2020	0.926*** (0.016)	0.909*** (0.024)	0.951 (0.060)	0.856*** (0.025)	0.863*** (0.020)	1.012 (0.023)
2021	0.794*** (0.020)	0.675*** (0.020)	1.026 (0.090)	0.852*** (0.024)	0.680*** (0.022)	0.990 (0.026)
Observations	4,194,803	2,601,916	551,159	1,041,673	2,429,687	1,763,280
Log Likelihood	-2,512,297	-1,394,694	-328,607.48	-595,220.73	-1,426,290	-1,033,297

Notes: This table presents the results of logit regressions estimating the probability of re-enrollment by area of study, degree level, and year of university study, as well as graduation rates. Year numbering is expressed as the odd-ratio with the 2019 as a reference. Each panel reports odds ratios for different subgroups of students. Panel A focuses on re-enrollment by area of study and degree level, Panel B on re-enrollment by year of university study, and Panel C on graduation rates. Standard errors (in parentheses) are clustered at the university level, and asterisks indicate significance levels (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$. Observations and log likelihoods for each subgroup are also provided.

effect of the pandemic is therefore limited to the demographics that have shown stability, namely gender and free lunch status. We find that the gender gap reduces over time, reaching pre-pandemic levels for female. While we do not observe a growing gap based on socioeconomic status, we find a decline in enrollment for students with free lunch status. This result suggests that COVID-19 is likely to induce a growing gap between underprivileged students and the rest of the student population, a concern given that this group has lower economic and educational opportunities. We replicate the analysis using the likelihood to graduate, as presented in Fig. C.1 in Appendix C. Our results highlight that students with free lunch status are more strongly impacted by a lasting effect on the likelihood of graduating. This is also confirmed for students from middle-low and middle-high SES backgrounds, who are less likely to graduate compared to students from high SES backgrounds.

5.5. Policy stringency and university dropout

In Section 5.1, we compare different years to assess the impact of COVID-19 on university dropout. But this approach lacks precision in analyzing the effect of lockdown policies on academic dropout. To address this limitation, we employ a natural experiment that occurred in France at the end of the first lockdown, as described in Section 4.2.

This institutional setting provides the opportunity to evaluate the extent to which the severity of the pandemic and the stringency of the resulting policies impacted students' enrollment behaviors. We begin by conducting a pre-trends analysis to confirm that the red and green zones exhibited similar dropout dynamics before the pandemic. We also compare student characteristics between the two zones to ensure a balanced treatment based on these attributes (see Table B.3 in Appendix B.6). Finally, we present our primary analysis and conduct robustness checks to validate the findings.

Fig. 6 presents dropout and graduation probabilities from the academic year 2012 to 2020. The trends in differential dropout rates in the two zones prior to the pandemic exhibit are similar, with no noticeable differences observed. Table 5 presents the difference-in-difference estimates which we use to evaluate the extent to which the stringency of disease lockdown policies impacted dropout and changed graduation rate. We therefore report the estimates derived by using Eq. (2) on data from different timespans. We first constitute a control group consisting of all available student-years (i.e. from 2013 to 2019 inclusive), and then use just the academic year 2019, the cohort most likely to be close to the next, pandemic year, as the control. We then extend the timespan of the control group by one year in Column (4), and then by two years in Column (5).

Our estimates reveals that policy stringency causes a decrease of about 3,8% in enrollment rate in 2020. To put this result into perspective, the impact of the additional policies implemented for one

Table 5
Policy stringency and university drop-out.

Panel A. Enrollment					
	2013 to 2019 (1)	2013 to 2019 (2)	2019 (3)	2018 to 2019 (4)	2017 to 2019 (5)
2020	0.937*** (0.010)	0.939*** (0.008)	0.978*** (0.008)	0.979*** (0.008)	0.975*** (0.008)
Red	1.069** (0.033)	1.155*** (0.037)	1.146*** (0.040)	1.147*** (0.039)	1.155*** (0.039)
2020 × Red	0.972 (0.025)	0.978 (0.017)	0.962** (0.019)	0.970* (0.016)	0.967** (0.014)
Constant	3.710*** (0.137)	6.733*** (0.235)	5.661*** (0.192)	5.786*** (0.193)	5.894*** (0.203)
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	12,510,282	12,510,282	3,101,736	4,542,668	5,953,177
Log Likelihood	-7,027,355	-7,000,741	-1,790,323	-2,605,139	-3,397,340

Panel B. Graduation					
	2013 to 2019 (1)	2013 to 2019 (2)	2019 (3)	2018 to 2019 (4)	2017 to 2019 (5)
2020	1.133*** (0.034)	1.110*** (0.029)	0.958** (0.020)	1.015 (0.016)	1.038* (0.020)
Red	0.892** (0.044)	1.002 (0.025)	1.095** (0.039)	1.050 (0.036)	1.034 (0.034)
2020 × Red	0.995 (0.048)	0.983 (0.041)	0.928*** (0.026)	0.956 (0.027)	0.979 (0.033)
Constant	2.394*** (0.172)	2.597*** (0.129)	2.937*** (0.174)	2.439*** (0.136)	2.596*** (0.144)
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	3,716,375	3,716,148	917,827	1,345,357	1,767,157
Log Likelihood	-2,263,726	-2,221,434	-525,900.88	-780,479.16	-1,033,637

Notes: This table reports estimates of the likelihood of re-enrollment for the following year and graduation among students who experienced more stringent COVID-19 policies in the first lockdown extension period (i.e. studying in a red zone) relative to students who experienced less stringent policies (i.e. studying in a green zone). For panel A, the sample covers all students enrolled in a university degree in France between the initial year mentioned for the control sample in each column and 2020. For panel B it consists in all students enrolled in a graduation year in a university degree program in the corresponding years. Each column presents a logit regression performed separately for a given control group time window. The regression includes university fixed effects (to account for differences in university quality) and the student characteristics listed in Table 1. The dropped observations between columns (1) and (2) of Panel B result from universities where the graduation rate is perfectly predicted. Standard errors (shown in parentheses) are adjusted for clustering at the university level. Asterisks indicate traditional levels of statistical significance (***, **, *, for 0.01, 0.05, 0.1, respectively).

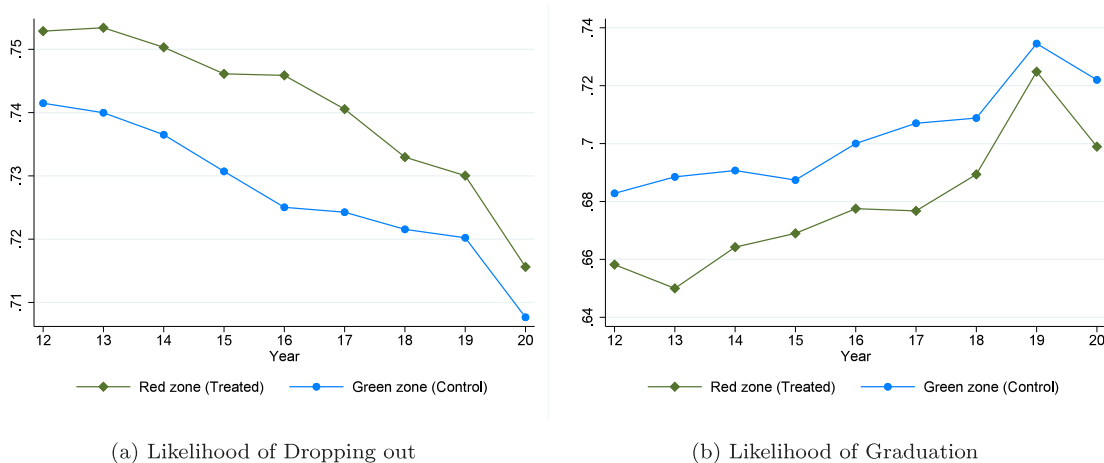


Fig. 6. Pre-trends in green and red zones.
Notes: The figure presents the pre-trend analysis for the likelihood of dropping out and graduating for each zone impacted by the natural experiment in France. The measures are for re-enrollment behaviors and graduation rate at the individual level. Each dot represents the average of all areas within each zone for the corresponding year.

month is comparable in scale to the average effect of the COVID-19 pandemic itself. However, this result is sensitive to the time-span that

is considered. For instance, the 2020 × red odd ratio's is not statically significant different from one when considering all the year available, while restricting to more recent years indicate a negative effect of policy stringency on enrollment behaviors. Concerning the likelihood of graduating, we observe a decline when the previous academic year is used as the control. This effect might be driven by the spike in the graduation rate that occurred in the year preceding the COVID-19 pandemic (see Fig. 6(b)). With control groups including more than one pre-pandemic year, we do not find evidence of an effect of policy stringency on graduation.

We then conduct several sensitivity checks to assess the robustness of our findings. Initially, we examine an alternative measure of the treatment variable, where the reference group is constituted by taking the average dropout rate for all the available years before the COVID-19 pandemic. Furthermore, we investigate the results by separating the Ile-de-France region, including Paris and the surrounding area, from the rest of the red zone (see Table D.1 in Appendix D). This differentiation is due to the unique characteristics of the Ile-de-France region, where universities are highly concentrated and differ significantly both in terms of their selectivity and in the contents' of their degree from those in the rest of the country. Interestingly, the restriction to students which are not based in Ile-de-France turns the 2020 × red's coefficient insignificant, which may suggest that the former effect is mainly driven by students living in Paris' area.

5.6. Potential mechanisms

5.6.1. Labor market and local pandemic situations

Here we examine two potential factors that may have influenced individual decisions to withdraw from university: the labor market conditions at the end of the 2020 academic year, and the severity of the local pandemic situation in 2020.¹² As highlighted by the seminal work of Becker (1964), the decision to pursue an additional year of study involves weighing the potential returns against the associated opportunity costs. The COVID-19 pandemic significantly reduced labor market opportunities for students. According to this theoretical framework, these unfavorable economic conditions should make students more likely to extend their enrollment in university for an additional year. Conversely, more severe local pandemic conditions may be expected to impose a greater mental burden on students (e.g. Guse, Weegen, Heinen, & Bergelt, 2021), which could decrease their likelihood of enrolling for the following academic year.

To assess the potential impact of these mechanisms, we use administrative datasets that offer detailed geographical and temporal granularity (see Appendix A). We measure labor market opportunities using quarterly unemployment rates at the finest geographical unit of analysis for which unemployment rate data are available in France, the “employment zone” - “Zone d'emploi” - (or “labour market area”) level.¹³ We begin by calculating the quarterly unemployment rate during the period in each year from 2016 to 2020 when students decided whether to re-enroll for the upcoming academic year. We then determine the difference between these specific quarterly rates and the

¹² Replicating the spatial and university-level mechanisms is challenging due to the decentralized response during the second year of the pandemic in France. While the 2020 school year started normally, the second COVID-19 wave in October 2020 led to regional lockdowns and varied restrictions, adding noise to our estimates. Universities could choose hybrid or fully online classes, with decisions reflecting local conditions. This variation, along with regional factors like employment zones, complicates the analysis of student enrollment behavior.

¹³ An employment zone (or labor market area) is a geographic unit whose boundaries are chosen to delimit an area that includes both the workplace and the residence of the majority of a local labor force. INSEE divides France into 306 employment areas, which are used to study local labor markets. <https://www.insee.fr/fr/metadonnees/source/indicateur/p1660/description>.

structural level of unemployment, measured as the average over the years 2016–2019. We take a similar approach to calculate local exposure to the pandemic, using excess mortality.¹⁴ These calculations are based on a dataset of individual death records from January 1, 2018, to December 31, 2020 from the “Fichier des Décès Quotidiens” (daily record of deaths).¹⁵ The indices for calculating unemployment rates and local pandemic severity are presented in Eqs. (4) and (5), respectively. This approach has the advantage of quantifying the relative difference between the value of the variables of interest in the COVID-19 year and their structural level as measured in the previous year.

$$UR_{ze} = \frac{UR_{ze}^{2020} - [0.25 \times \sum_{i=2016}^{i=2019} UR_{ze}]}{UR_{ze}^{2016}} \quad (4)$$

$$D_{ze} = \frac{N_{ze}^{2020} - [0.5 \times (N_{ze}^{2018} + N_{ze}^{2019})]}{Population_{ze}^{2014}} \quad (5)$$

UR_{ze} can be interpreted as the change in the unemployment rate compared to the structural unemployment rate as measured for the corresponding year in a given employment zone ze . Positive values reflect a decrease in employment during the pandemic, which occurred in many employment zones due to various French government policies aimed at mitigating the impact of the pandemic on the labor market. D_{ze} can be interpreted as excess mortality due to the COVID-19 pandemic, in comparison to its structural level, defined as mortality (rate of deaths in the population) in 2014. Fig. 7 presents the geographical distribution of excess unemployment and excess mortality.

The left panel of Fig. 7 shows a lighter color in eastern France, indicating a greater increase in mortality during the first year of the pandemic in this region. This finding is consistent with the results of Brandily et al. (2021). It may be explained in part by the greater spread of the disease in this area during the early stages of the pandemic, leading to increased mortality. But the right panel of Fig. 7 does not show any clear geographical concentration of excess unemployment. Our findings reveal that unemployment rates were higher in regions with stricter policies (two-sided t-test, $p < 0.001$), as was excess mortality (two-sided t-test, $p < 0.001$). Fig. E.1 in Appendix E provides a more comprehensive analysis of the relationship between the two potential mechanisms. The absence of a geographical relationship between unemployment and pandemic intensity is particularly significant, as it allows us to distinguish between their impacts on students' enrollment decisions.

Fig. 8 illustrates the relationship between the unemployment rate, excess mortality, and enrollment and graduation rates at the employment zone level. Our approach to calculating enrollment outcomes is similar to the approach we take to calculate excess unemployment and mortality. In other words, we compute the standardized difference in enrollment behaviors between the COVID-19 cohort and previous years, expressed as a rate relative to enrollment behaviors in 2012, the first year available for analysis. This approach has the advantage of quantifying the extent to which the COVID-19 cohort altered its enrollment behaviors at a fine-grained geographical level, while taking into account inherent structural variations in students' behaviors. Our dataset specifies three locations for each student at the employment zone level: their university, their residence, and their parents' residence. We focus specifically on the employment zone associated with

¹⁴ At the beginning of the pandemic, testing capacities and strategies varied considerably by region and time (Balmford, Annan, Hargreaves, Altoè, & Bateman, 2020; Kung et al., 2021; Rivera, Rosenbaum, & Quispe, 2020; Silverman, Hupert, & Washburne, 2020; Yorifuji, Matsumoto, & Takao, 2021), even in France. We thus follow Brandily et al. (2021)'s in measuring local exposure to the pandemic through excess mortality, which provides a metric of the local severity of the pandemic that is not biased by those variations.

¹⁵ Individual death records are available at the municipal level. We then aggregate this municipality information at the employment area level in order to match the territorial division used for unemployment rates.

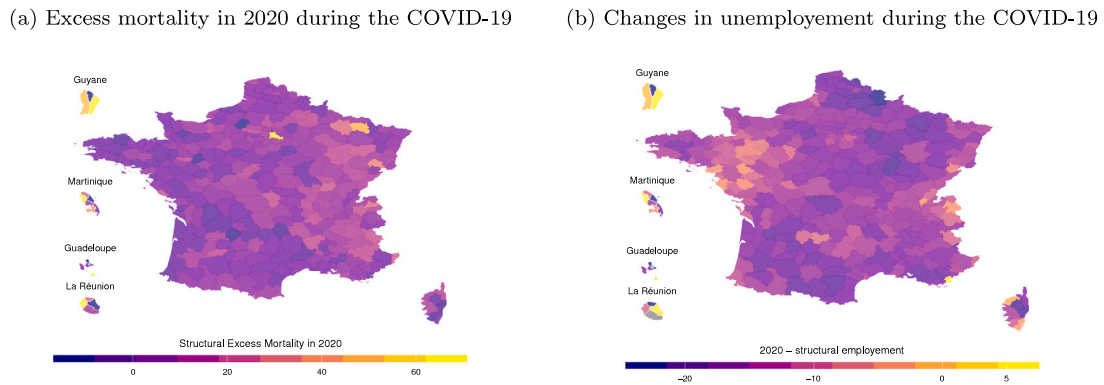


Fig. 7. Geographical distribution of excess mortality and unemployment.

Notes: The figure presents the geographical distribution of our two main mechanisms measured at the employment zone level: excess mortality and excess unemployment. The employment zone is the smallest geographical unit for which unemployment rate data is available. There are 306 such zones in France, excluding some DOM-TOM regions such as Mayotte. For both variables, we calculate the difference between the value for the period under scrutiny and the mean for the previous year, and then divide it by the population rate/unemployment rate in the initial period.

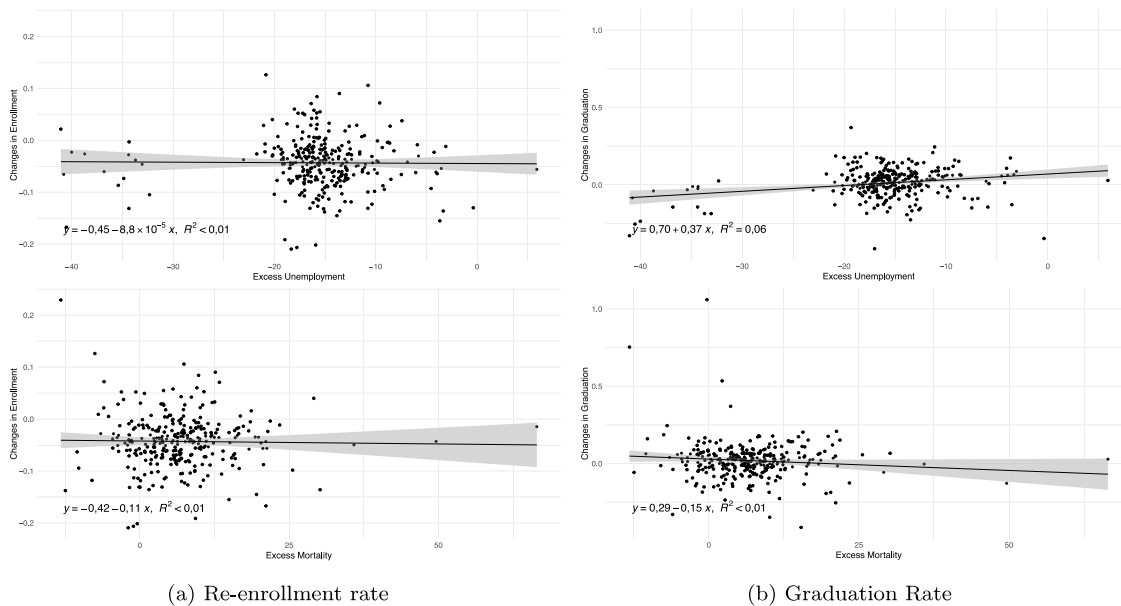


Fig. 8. Mechanisms behind changes in enrollment and graduation rate at the employment zone level.

Notes: The figure illustrates the relationship between two potential mechanisms and our two main outcome variables. The left-hand side of the figure shows the likelihood of re-enrollment, while the right-hand side shows the likelihood of graduation. The upper panel on each side depicts the relationship between excess unemployment and the variable of interest, while the bottom panel represents the relationship between excess mortality and the variable of interest. Each dot in the figure represents an observation at the employment zone level, the unit for which we calculate the structural change in enrollment and graduation rates. The line in the figure represents a linear fit based on the equation presented in the corresponding panel.

the municipality of the university, assuming that students are likely to seek employment opportunities near their educational institution. Fig. 8(a) presents the relationship between re-enrollment and these plausible mechanisms, while Fig. 8(b) replicates that analysis for the graduation rate.

Fig. 8(a) does not provide compelling evidence that either unemployment or mortality determined enrollment behavior, either in terms

of effect size or explanatory power. These findings suggest that neither recent variation in local employment opportunities nor the local severity of the pandemic played a role in determining university students' decisions on whether or not to re-enroll. Fig. 8(b) shows a relationship between the local unemployment rate and students' likelihood of graduating. An increase of one point in excess unemployment is associated with an 0.37-point increase in the likelihood of graduating. However,

no evidence was found of a relationship between intensity of exposure to COVID-19, as measured by local excess mortality and the likelihood of graduating. Appendix F presents similar analyses for both of the other locations characterizing the students: their place of residence and that of their parents, with similar results (see Figs. F.1–F.3).¹⁶ No conclusive evidence was found of any impact of these mechanisms on the probability of being present for at least one exam.

5.6.2. University quality and enrollment behaviors

The capacity of universities to support student progression is crucial, particularly during the COVID-19 pandemic. Higher-quality universities are likely to offer better learning environments, with more engaged teachers and additional resources to aid academic development. However, our initial estimates absorb university quality through fixed effect estimates, limiting our ability to explore this aspect in greater detail. To address this, measuring university value-added, similar to the approach in Cunha and Miller (2014), could provide valuable insights, although data limitations prevent us from doing so. Such an approach would require ranking at a national standardized exam and corresponding metrics at the end of university education. For these reasons, we propose three alternative measures to gauge the impact of university quality on enrollment behaviors.¹⁷

The first measure employs a data-driven approach to assess a university's ability to retain students from one year to the next. Specifically, we adopt an alternative method based on Eq. (1), where we interact each university with a year fixed effect for all institutions prior to the pandemic. This approach yields a coefficient for each university that represents its average ability to retain students for the following year. This method builds on the literature related to estimating group effects using fixed-effect models (e.g. Shang & Lee, 2011), which offers the advantage of measuring a university effect that accounts for differences in cohort composition at a year \times university level. The resulting coefficients are comparable under the assumption that the student population did not undergo significant changes across specific universities. Each parameter estimated at the university \times year level provides insight into the relative importance of each observation on enrollment behaviors.¹⁸ By averaging these estimates across all pre-pandemic years, we obtain an indirect measure of university quality.

We ensure the robustness of our results by subsequently assessing two other measures of university quality based on graduates' integration into the labor market. These measures are economically relevant

¹⁶ The equivalent results of these different analyses can be understood in terms of two main explanations: (i) students' location is similar across measures, and (ii) the (lack of) effect is consistent across measures.

¹⁷ We acknowledge that an alternative approach might involve considering international rankings of higher education institutions, such as the "Times Higher Education" or the "Academic Ranking of World Universities". While these rankings offer the convenience of being easily understandable for a broader audience, they lack granularity for institutions that are not highly competitive at the international level. For example, 2 out of the top 8 universities are ranked between 301 and 350, which makes it difficult to derive a granular index. Moreover, these rankings emphasize research-intensive universities and prioritize research indicators, which do not comprehensively represent the broader aims of all universities.

¹⁸ Our data-driven measure of university quality in preventing dropout assumes that the number and identifiers of universities remain constant over time. However, over the last decade, the French government has actively pursued university mergers, resulting in an incomplete measure of university quality using this approach. Of the 165 universities identified during the study period, we were able to obtain consistent quality data for 69 universities for the entire period. Additionally, we have data for 105 universities before the pandemic, which is merged with the "Enquête nationale sur l'insertion professionnelle des diplômés de Master." Thus, we can make comprehensive comparisons for 69 universities, while the training stage includes a larger number of observations.

as they capture both salary levels and employment rates at the university level. We consider two labor market outcomes: the difference between the salary 18 months after graduation and the median regional salary, and the share of students who enter the labor force. The first measure captures the competitiveness of graduate students compared to the regional salary scheme, while the second accounts for a broader definition of labor market integration. We use the "Enquête nationale sur l'insertion professionnelle des diplômés de Master" from 2010 to 2019, a survey in which students report their employment status and salary, aggregating this data at the university level. However, this methodology has two limitations: firstly, the survey's declarative and mandatory nature may introduce biases, as students with better working conditions are more likely to respond; secondly, it is confined to students graduating from master's degrees, which may not fully represent overall university quality. Additionally, this approach does not address issues related to student selection at specific universities, where students with higher academic performance are more likely to enroll. Despite these limitations, this robustness check allows us to measure university quality in terms of labor market opportunities.

As in Section 5.6.1, we calculate the difference between the dropout rate observed during the pandemic and the average dropout rate before the pandemic. This measure accounts for systematic differences in enrollment behavior at the university level. We express this variable as the excess dropout for the COVID-19 cohort relative to the structural dropout rate. First, we present the relationship between our preferred data-driven measure of university quality and excess enrollment observed in the first year of the pandemic. We then replicate this analysis using raw data from the "Enquête nationale sur l'insertion professionnelle des diplômés de Master."

Fig. 9 displays the difference in enrollment compared to the average observed during the 2012–2019 period using the data-driven measure of a university's ability to prevent dropout rates. We do not find a meaningful relationship between the excess dropout rate for the cohort exposed to the pandemic and the data-driven measure of university quality based on pre-pandemic years. Although a negative slope might appear, it is driven by outliers from universities with specific enrollment behaviors, such as those with particularly high or low enrollment rates prior to the pandemic. We assess the robustness of this finding using two alternative measures of university quality — e.g., labor force participation in Panel B of Fig. 9 and wage levels in Panel C of Fig. 9 — and find consistent results, indicating no relationship between quality and enrollment behaviors during the pandemic. Our results consistently show no relationship between university quality and enrollment behaviors, suggesting that these behaviors were primarily influenced by global or individual factors rather than by university characteristics.

5.6.3. Alternative mechanisms

We briefly discuss alternative potential mechanisms that may explain students' behaviors, which we are unable to examine due to the limitations of the administrative data used in our empirical approach. Specifically, we consider three key aspects that may have influenced our results: mental health, housing conditions, and digital literacy.

One prominent aspect is the severe impact on students' mental health during the pandemic. This effect may occur directly by inducing heightened stress levels due to exposure to the disease, which tends to decrease pro-social behaviors (Terrier, Chen, & Sutter, 2021). Moreover, the pandemic indirectly affects mental health through lockdown policies and the overall stressful environment created by constant media coverage. There is ample evidence indicating that the pandemic has heightened the risk of students facing severe mental health challenges (Ford, John, & Gunnell, 2021). For example, Arsandaux et al. (2021) demonstrate that students in France have experienced increased depressive and anxiety symptoms, as well as suicidal thoughts. Consequently, it is likely that the COVID-19 pandemic and its associated lockdown measures have significantly impacted youth well-being, leading to an elevated likelihood of dropout.



Fig. 9. University quality and excess dropout during the pandemic.

Notes: The figure illustrates the coherence of our university quality measures and their association with excess dropout rates during the COVID-19 pandemic. The dependent variable (y-axis) is consistently the excess dropout rate measured during the first year of the pandemic, and each panel displays its relationship with several measures of university quality. Panel A shows the relationship between the excess dropout rate and a data-driven measure of university quality based on university \times year fixed effects. Panels B and C depict the correlation between two variables derived from the “Enquête nationale sur l’insertion professionnelle des diplômés de Master” (the percentage of graduates entering the job market and the average salary difference 18 months post-graduation, aggregated at the university level) and the excess dropout rate observed during the pandemic.

Another potential mechanism is the impact of students’ living conditions on their learning experiences during the pandemic, which may have led those with inadequate housing facilities to be more likely to drop out. For instance, Brandily et al. (2021) demonstrates that poor housing conditions were associated with increased disease transmission. Additionally, residing in cramped quarters might exacerbate the pandemic’s mental health burden, particularly for students lacking privacy, prompting some to pause their education due to challenging study conditions.

A final factor that may have influenced learning during the COVID-19 pandemic is students’ digital literacy — their proficiency in using digital devices — given the need to navigate new tools and online meeting platforms. While there has been a narrowing gap in socioeconomic status regarding the availability of digital devices at home (Bulman & Fairlie, 2016), students may still vary in their ability to effectively utilize them, potentially leading to reduced learning outcomes and a higher likelihood of dropout.

Students’ perceptions of the COVID-19 pandemic are influenced by their views on education, which are likely multifactorial, making it challenging to pinpoint all the mechanisms at play. For instance, inadequate housing facilities could increase exposure to the disease, potentially leading to a decrease in students’ prosocial behaviors and subsequently lower enrollment in the following year. While this rationale is supported by the literature, empirically documenting such relationships is difficult due to the intertwined dimensions of interest—a challenge that is beyond the scope of this paper.

6. Conclusion

Drawing on a comprehensive dataset encompassing all university students in France from 2012 to 2022, this paper provides evidence that students’ likelihood of dropping out increase during the pandemic. Specifically, the initial findings reveal a 3.7% decrease in the chances of re-enrollment for the first COVID-19 cohort compared to the previous year’s cohort. This is equivalent to the cumulative decline observed in French higher education institutions over the preceding decade. This decline cannot be attributed to changes in grading practices or attendance at final exams, indicating a genuine decrease in re-enrollment rates. The impact is predominantly observed among male students, those of non-French nationality, and those who do not qualify for free lunch, as well as affecting first-year university students. These findings suggest that pandemic-induced dropouts may have adverse effects on employment opportunities for these groups of students.

Our analysis reveals that the COVID-19 pandemic led to a medium-term shift in enrollment behaviors, with significant impacts observed

across different fields of study and student demographics. Notably, first-year students, as well as those in their third and fifth years of study, and Ph.D. students, experienced substantial declines in re-enrollment rates. While the gender gap in enrollment showed signs of narrowing to pre-pandemic levels, disparities persisted for underprivileged students, particularly those with free lunch status. Overall, these findings suggest that the pandemic’s effects on higher education were not uniformly distributed.

We then refined the analysis by leveraging a natural experiment in France, where policies of differing stringency were implemented in different areas to contain the spread of the virus during the first wave of the pandemic. This setting provided the opportunity to analyze whether and how the intensity of lockdown policies influenced students’ educational outcomes. Leveraging this quasi-natural experiment, we find evidence that stringent policies increased dropout rates.

In addition, we conducted our analysis at a detailed geographical level, examining whether local labor market opportunities or the local severity of the pandemic itself induced significant changes in enrollment behaviors. We did not find evidence supporting the idea that re-enrollment was influenced by either factor. Last, we considered university quality as a possible mediating factor of dropout behaviors, where we did not detect any statistical relationship. Overall, the decision to pursue or to quit university appears to be shaped more by individual characteristics than by university quality or residential location. This suggests that students’ decisions in times of crisis are more likely to be driven by their perceptions of the situation rather than by institutional factors. The fact that individual characteristics shape dropout decisions suggests that policies aimed at fostering resilience could have altered the impact of the COVID-19 pandemic on university enrollment, as documented by RCTs based on behavioral nudges targeting vulnerable populations (Lichand, Christen, & van Egeraart, 2023).

The findings of this study carry important policy implications for educational institutions and policymakers. First, the observed decrease in university re-enrollment rates in the COVID-19 cohort highlights the need for targeted support and interventions for students facing challenges during pandemics. Counseling services, financial assistance programs, and mental health support could help mitigate the negative impact of such external shocks on students’ educational trajectories. Second, the significant effects of lockdown stringency on enrollment behaviors calls for nuanced policy responses, balancing disease lockdown measures with educational continuity. Additionally, policies targeting first- and second-year undergraduate students, who were the most affected by the pandemic, could focus on personalized support and guidance during these critical stages of their academic

journey. Finally, given the exacerbation of inequalities among university students during the pandemic, policymakers should prioritize measures that address structural barriers, support underprivileged students, and promote equal access to quality education. Incorporating these policy implications into strategic planning may help policymakers effectively respond to the challenges brought about by pandemics and work towards a more resilient and inclusive higher education system.

The study has identified several potential areas for future research, in light of its limitations. First, conducting cross-country comparative analyses could reveal common patterns and variations in enrollment decisions and dropout rates across different educational systems. Second, examining the long-term labor market effects of the pandemic on students' career trajectories¹⁹ and economic prospects should provide insights into potential disparities in labor market outcomes. Third, exploring the role of mental health and well-being in enrollment behaviors and academic performance during the pandemic could offer insight into valuable support measures for students. Finally, investigating the influence of demographic factors on university dropout should deepen our understanding of how external shocks interact with individual characteristics, and contribute to existing knowledge on inequalities in higher education. Together, these further studies should enrich our understanding of the multifaceted impact of the COVID-19 pandemic on higher education and its implications for students' futures.

Overall, our findings suggest that the COVID-19 pandemic has had a significant impact on university student dropout rates in France, varying across demographic characteristics, fields of study, and institutional contexts. Understanding these impacts is crucial for addressing the challenges facing students and mitigating the exacerbation of inequalities in higher education. Further research and policy efforts are needed to support students and promote equitable access to education during and beyond the pandemic.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve the clarity of the writing. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

None.

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Appendix A. Variables and data-sets used

¹⁹ See [Issehnane and Moulin \(2024\)](#) for the short-term effects of the pandemic on the employment situation of young graduates.

- Excess unemployment at the employment area level: “*Taux de chômage localisés (par régions, départements et zones d’emploi)*” INSEE (France’s National Institute of Statistics and Economic Studies) estimates unemployment rates in France on a quarterly basis, excluding Mayotte. The numerator in the national rate calculation is the estimated number of unemployed individuals in the country (excluding Mayotte) on a quarterly average basis, obtained from data collected through INSEE’s annual CVS (Cadre de vie et Sécurité, or Living environment and safety) survey. The denominator is the total size of the national labor force, including both employed and unemployed individuals. To calculate localized numbers of unemployed individuals by employment area (here, excluding both Mayotte and French Guiana), the number of unemployed individuals used as the numerator in the national rate is distributed proportionally to the monthly number of officially registered jobseekers with no paid employment in each employment area, separately by gender and for three age groups (age 24 or under, ages 25–49, age 50 or over). The resulting data is adjusted for specific seasonal fluctuations in each employment area, as well as the numbers of unemployed individuals in the department or region within which the employment area is situated as measured by the CVS survey. INSEE estimates the number of employed individuals in each area (by place of residence) based on data from three sources: quarterly localized employment estimates, annual estimates of numbers of employed individuals by place of work (drawn from administrative sources as gathered and processed by INSEE’s ESTEL system), and census data. It is estimated quarterly and adjusted to match employment figures for the department or region within which the employment area is situated. <https://www.insee.fr/fr/statistiques/1893230#consulter>.
- Excess mortality: The “*fichier des décès quotidiens*” (daily death records) (daily death records) contain information on all deaths that occurred between January 1st, 2018 and June 5, 2020. Each record includes various details about the death, such as the date, municipality, and type of place of death (e.g., hospital, home, nursing home, etc.). Information about the individual, including their department of residency, gender, and date of birth, is also recorded. During the COVID-19 crisis, INSEE increased the frequency of publication of these records. As a result, some compromises were made in terms of quality checks. The records are initially collected by municipalities, and then gradually incorporated into the INSEE datasets as they are provided by the municipalities. It is possible that the records were not complete at the time of our analysis, despite regular updates. For more information and access to these files, please refer to the following URL: <https://www.insee.fr/fr/statistiques/4487854>.
- Population density: Large variations in the spatial extent of municipalities and the distribution of population within them can undermine the usefulness and comparability of population density figures calculated based on administrative boundaries. To solve this problem, France’s municipal density grid instead divides the territory into 1 km × 1 km cells and measures population sizes within them, identifying population agglomerations. Municipalities are characterized in terms of the size of these agglomerations, rather than the overall population density within their administrative boundaries. This classification aligns with Eurostat framework, introducing an additional category for very sparsely populated areas, which are more common in France than in other European countries. On the basis of the density grid, municipalities are divided into four categories: high, intermediate, low, and very low density. High and intermediate density municipalities are classified as urban, while low and very low density municipalities are classified as rural. Population data are drawn from INSEE’s Fidéli database of housing and individual demographic files. The density grid was updated in 2020 to align it with European methodology. The current method used to

produced it is harmonized with the definition of the boundaries of city functional areas (*aires d'attraction des villes*) as defined in the division of the territory based on the 2020 population census (*zonage en aires d'attraction des villes*). The downloadable file provides the composition of the density grid by municipalities as defined on January 1, 2022, along with the distribution of the population at the four density levels. <https://www.insee.fr/fr/information/2114627>

- Labor market area (“*Zone d’emploi*”): An employment zone (or labor market area) is a geographic unit whose boundaries are chosen to delimit an area that includes both the workplace and the residence of the majority of a local labor force. INSEE divides France into 306 employment zones, which are used to study local labor markets, and are the territorial unit for which localized employment and unemployment rates are calculated. The division of employment zones covers both metropolitan France and the French overseas departments. The latest classification is based on commuting patterns observed during the 2016 census. The algorithm used to divide the country into employment zones is the Eurostats-recommended open source tool LabourMarketAreas. <https://www.insee.fr/fr/information/4652957>
- Students’ Labour market integration (“*Enquête nationale sur l’insertion professionnelle des diplômés de Master*”). This survey, conducted since 2010 by the Ministry of Higher Education, aimed to collect information on the transition of master’s graduates to the labor market. It targeted students who obtained their master’s degree and entered the labor market within one year of graduation, achieving an overall response rate of about 70 percent. Master’s graduates were asked to report their annual earnings 18 months after graduation.

Appendix B. Heterogeneity analysis

This section presents the heterogeneity analysis based on the field/level of study and students’ demographics. Appendix B.1 replicates the main analysis for students who are not enrolled as interna-

tional students. Appendix B.6 presents the balance table between the Green and Red zones to test the exogeneity assumption. Appendix B.2 presents the pre-trend analysis for the three dependent variables and the dimension of heterogeneity under scrutiny. Appendix B.3 replicates the main analysis by field of study. Appendix B.4 provides descriptive statistics by the year of study to determine whether the association is due to demographic changes between years or differences in academic experience. Appendix B.5 shows the heterogeneity analysis based on students’ demographics in terms of likelihood to graduate and exam attendance.

B.1. Additional analysis for international students

See Table B.1.

B.2. Pre-trends analysis for the heterogeneity analysis

See Fig. B.1.

B.3. Analysis by fields of study (detailed)

See Fig. B.2.

B.4. Students’ characteristics by year of study

See Table B.2.

B.5. Demographics and educational outcomes

See Figs. B.3 and B.4.

B.6. Population characteristics between zones

See Table B.3.

Table B.1
Impact of COVID-19 on Non-exchange Students.

Panel A. Enrollment							
	Overall (1)	Non-STEM (2)	Soft-STEM (3)	Hard-STEM (4)	UG (5)	G (6)	Ph.D. (7)
2020	0.948*** (0.009)	0.960*** (0.010)	0.950* (0.026)	0.934*** (0.016)	0.890*** (0.009)	1.033* (0.018)	0.984 (0.039)
Observations	12,200,646	7,051,744	2,245,495	2,902,847	7,525,951	4,263,558	411,101
Log Likelihood	-6,786,202	-4,073,273	-1,024,844	-1,617,086	-3,946,573	-2,536,835	-231,798.83
Panel B. Graduation							
	Overall (1)	Non-STEM (2)	Soft-STEM (3)	Hard-STEM (4)	UG (5)	G (6)	
2020	0.919*** (0.016)	0.895*** (0.024)	0.947 (0.061)	0.848*** (0.027)	0.850*** (0.020)	1.014 (0.022)	
Observations	3,563,333	2,198,907	469,714	894,664	2,034,501	1,528,383	
Log Likelihood	-2,124,043	-1,166,515	-276,144.31	-508,546.18	-1,184,857	-897,659.31	
Panel C. Attendance							
	(1) Overall	(2) Non-STEM	(3) Soft-STEM	(4) Hard-STEM	(5) UG	(6) G	
2020	1.058 (0.045)	1.109*** (0.025)	1.036 (0.211)	0.990 (0.055)	1.206*** (0.080)	1.154*** (0.051)	
Observations	10,268,487	6,294,087	1,411,334	2,562,467	1,906,994	1,356,380	
Log Likelihood	-3,049,530	-1,885,291	-283,688.2	-822,513.37	-398,744.15	-356,499.01	

Notes: The table replicates the analysis carried out in Tables 2 and 3 for the subset of students not enrolled as international students. The estimates are based on a logit model with university fixed effects and standard errors clustered at the university level. Panel A presents the analysis on the probability of re-enrollment for the upcoming academic year, panel B on the probability of graduation, and panel C on the likelihood of attending at least one exam.

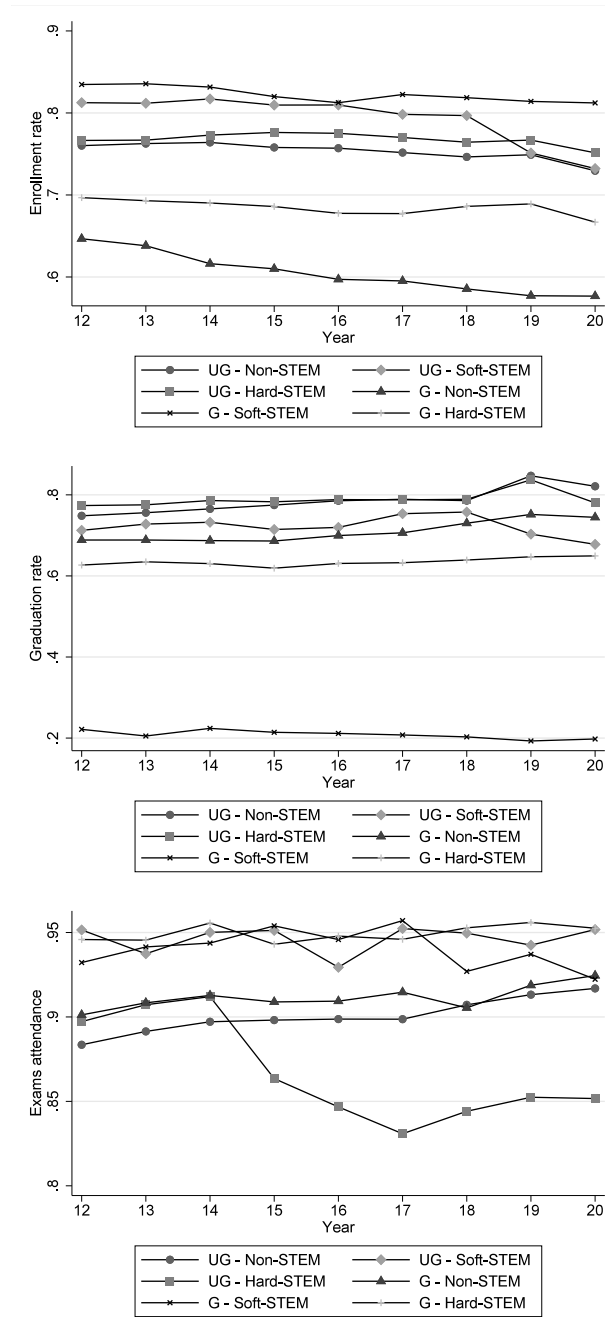


Fig. B.1. Pre-trend analysis on enrollment behaviors based on year/field of study.

Notes: The figure presents the yearly averages of our educational outcomes for each dimension under scrutiny. Each dot represents the average value of the respective outcome for the corresponding calendar year for each subgroup of interest. Enrollment is defined as 1 when an individual is observed in the subsequent academic year. The variable exam attendance takes a value of 1 if the individual attends at least one final exam, while graduation indicates whether the individual successfully obtained their degree at the end of a graduating academic year.

Table B.2
Students' characteristics by year of study.

	First year	Second year	Third year	Fourth year	Fifth year	Sixth year
Female						
17	0.555	0.557	0.567	0.595	0.590	0.546
18	0.555	0.558	0.569	0.598	0.589	0.544
19	0.585	0.586	0.591	0.592	0.586	0.544
20	0.585	0.592	0.597	0.596	0.585	0.548
Average	0.570	0.573	0.581	0.595	0.588	0.546
Low SES						
17	0.221	0.189	0.253	0.273	0.335	0.367
18	0.211	0.190	0.260	0.268	0.331	0.371
19	0.220	0.194	0.255	0.265	0.320	0.339
20	0.215	0.187	0.232	0.239	0.304	0.309
Average	0.217	0.190	0.250	0.261	0.322	0.347
Middle-Low SES						
17	0.251	0.238	0.222	0.191	0.166	0.101
18	0.252	0.235	0.218	0.192	0.166	0.101
19	0.251	0.238	0.224	0.188	0.168	0.105
20	0.253	0.245	0.232	0.196	0.174	0.111
Average	0.252	0.239	0.224	0.192	0.169	0.105
Middle-High SES						
17	0.208	0.207	0.189	0.171	0.154	0.116
18	0.220	0.209	0.189	0.172	0.156	0.116
19	0.224	0.217	0.195	0.174	0.156	0.122
20	0.228	0.225	0.205	0.180	0.160	0.125
Average	0.220	0.214	0.195	0.174	0.157	0.120
High SES						
17	0.319	0.367	0.336	0.365	0.345	0.415
18	0.317	0.366	0.333	0.368	0.347	0.412
19	0.304	0.352	0.326	0.374	0.356	0.434
20	0.304	0.343	0.330	0.385	0.361	0.455
Average	0.311	0.357	0.331	0.373	0.352	0.429
Free Lunch status						
17	0.413	0.389	0.324	0.308	0.200	0.022
18	0.408	0.386	0.320	0.305	0.203	0.022
19	0.386	0.313	0.221	0.255	0.195	0.021
20	0.391	0.325	0.163	0.015	0.010	0.001
Average	0.399	0.353	0.257	0.220	0.152	0.017
Non-French nationality students						
17	0.096	0.105	0.139	0.191	0.198	0.232
18	0.098	0.108	0.144	0.188	0.200	0.233
19	0.099	0.099	0.132	0.181	0.199	0.236
20	0.094	0.095	0.120	0.170	0.196	0.226
Average	0.097	0.102	0.134	0.183	0.198	0.231

Notes: The table presents the share of each demographic group by year of study from 2017 to 2021. The "Average" row indicates the mean share of students for each demographic category. Each cell shows the share of the respective demographic group (panel) for a specific year (row) and year of enrollment (column).

Table B.3
Cohort composition of red and green zones in 2020.

	Green zone	Red zone	Difference
Demographics			
Female	0.588	0.586	0.003**
Non-French students	0.134	0.124	0.010***
Free Lunch Status	0.212	0.219	-0.006***
Low SES	0.234	0.233	0.001
Middle Low SES	0.214	0.233	-0.019***
Middle High SES	0.203	0.200	0.003***
High SES	0.350	0.334	0.016***

Notes: Each row presents the average proportion of students studying in red and green zones during the 2020 academic year the categories listed on the left. Column (1) represents the cohort studying in the green zone during the first COVID-19 lockdown extension period, and column (2) represents the characteristics of the cohort in the red zone. Column (3) presents the difference in means using a two-tailed t-test, and asterisks indicate traditional levels of statistical significance (***, **, *, for 0.01, 0.05, 0.1, respectively).

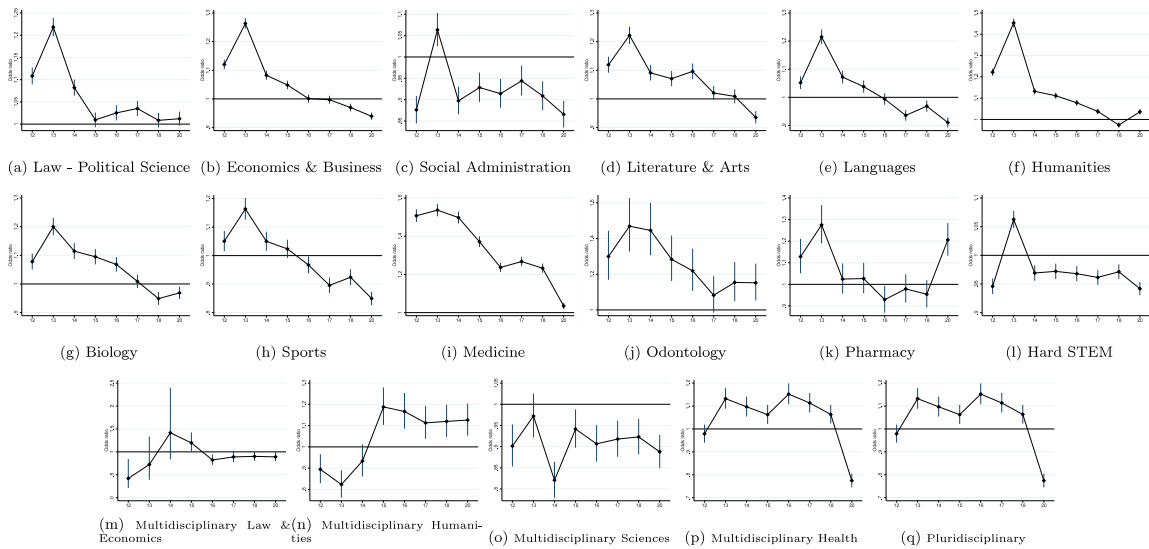


Fig. B.2. Pre-trend analysis on enrollment behaviors based on detailed field of study.

Notes: The figure illustrates changes in enrollment behaviors for each field of study based on a logit model (Eq. (1)). We cluster standard errors at the university level. The dependent variable in focus is the enrollment for the next academic year. The coefficient shown in the graph represents the odds ratio for the corresponding year. The reference year is the one preceding the pandemic. An odds ratio that does not overlap with the horizontal line indicates a significant change in the enrollment behaviors for students enrolled in the specific field during the pandemic. We compute the equation separately for each group and plot the relevant parameter on a separate panel to enhance readability.

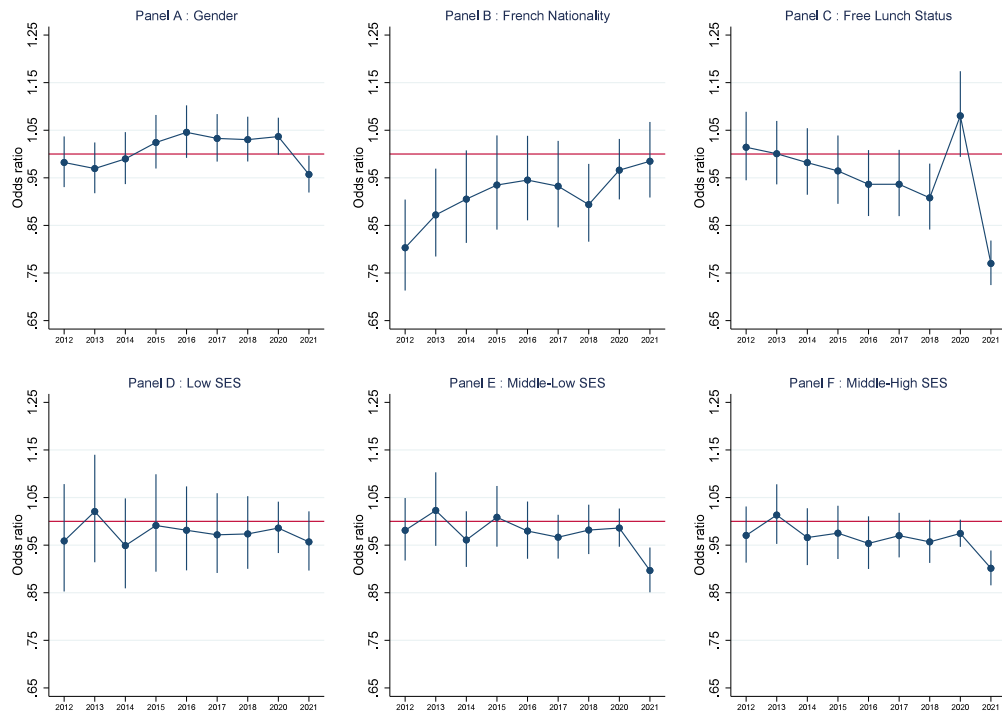


Fig. B.3. Heterogeneity in the likelihood of graduation.

Notes: The figure presents the heterogeneity analysis based on a logit model (Eq. (3)). We cluster standard errors at the university level. The dependent variable in focus is the likelihood of graduating. The coefficient shown in the graph represents the odds ratio for the interaction term between the demographic category and the year. The reference year is the one preceding the pandemic. An odds ratio that does not overlap with the red horizontal line indicates a significant change in the likelihood of graduation for members of the corresponding demographic during the pandemic. We calculate the equation for each demographics under scrutiny, and create a separate chart for each estimate to show the relevant parameter clearly. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Appendix C. Lasting effect of the pandemic on the likelihood to graduate - heterogeneity

Appendix D. Difference-in-differences without Ile-de-France

See Fig. C.1.

See Table D.1.

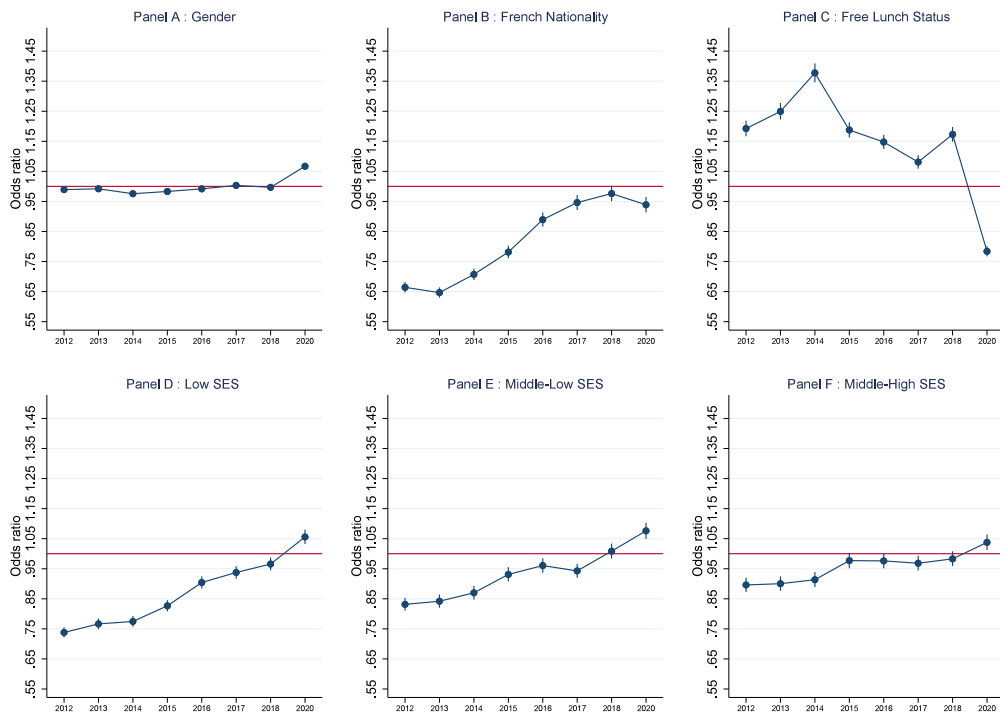


Fig. B.4. Heterogeneity on exam attendance.

Notes: The figure presents the heterogeneity analysis based on a logit model (Eq. (3)). We cluster standard errors at the university level. The dependent variable in focus is the exam attendance rate. The coefficient shown in the graph represents the odds ratio for the interaction term between the demographic category and the year. The reference year is the one preceding the pandemic. An odds ratio that overlaps with the red horizontal line indicates a significant change in the likelihood of exam attendance out for members of the corresponding demographic during the pandemic. We calculate the equation for each demographics under scrutiny, and create a separate chart for each estimate to show the relevant parameter clearly. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

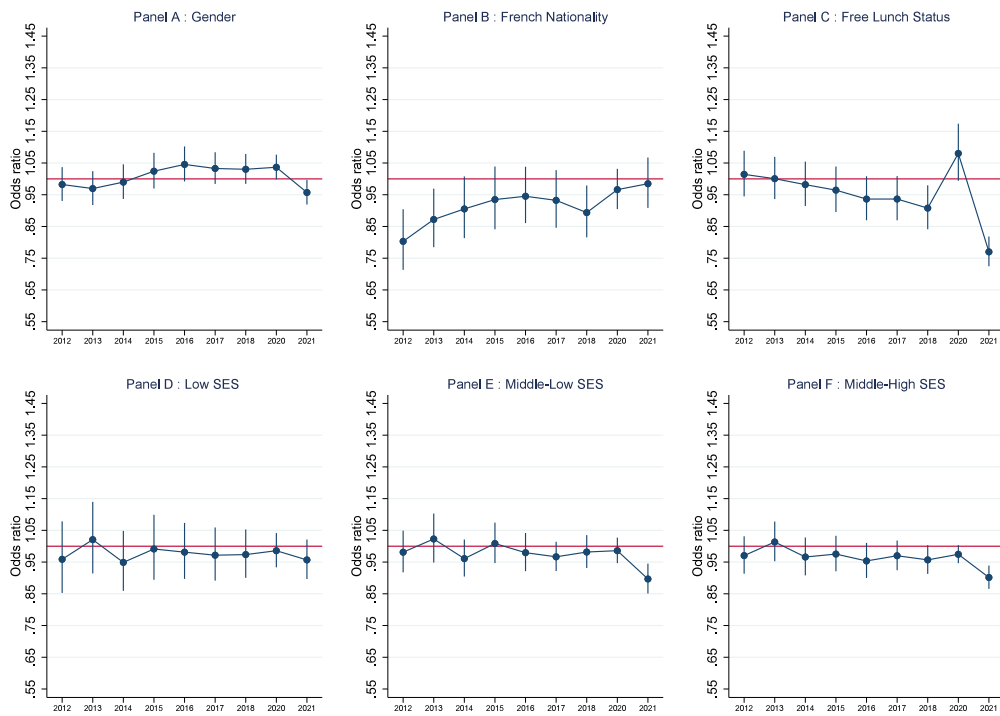


Fig. C.1. Lasting effect of the pandemic on the likelihood to graduate.

Notes: The figure presents the heterogeneity analysis based on a logit model (Eq. (3)). We cluster standard errors at the university level. The dependent variable in focus is the likelihood of graduating. The coefficient shown in the graph represents the odds ratio for the interaction term between the demographic category and the year. The reference year is the one preceding the pandemic. An odds ratio that overlaps with the red horizontal line indicates a significant change in the likelihood of graduation for members of the corresponding demographic during the pandemic. We calculate the equation for each demographics under scrutiny, and create a separate chart for each estimate to show the relevant parameter clearly. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table D.1
Did without Ile-de-France.

Panel A. Enrollment					
	2013 to 2019 (1)	2013 to 2019 (2)	2019 (3)	2018 to 2019 (4)	2017 to 2019 (5)
2020	0.938*** (0.010)	0.936*** (0.008)	0.979** (0.008)	0.979*** (0.008)	0.975*** (0.008)
Red	1.083* (0.045)	1.173*** (0.056)	1.145** (0.064)	1.151*** (0.061)	1.166*** (0.061)
2020 ×Red	0.971 (0.028)	0.969 (0.023)	0.977 (0.028)	0.980 (0.023)	0.967* (0.019)
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	9,774,499	9,774,499	2,434,088	3,560,658	4,666,091
Log Likelihood	-5,478,996	-5,456,545	-1,404,295	-2,039,765	-2,658,277
Panel B. Graduation					
	2013 to 2019 (1)	2013 to 2019 (2)	2019 (3)	2018 to 2019 (4)	2017 to 2019 (5)
2020	1.130*** (0.032)	1.112*** (0.031)	0.961* (0.021)	1.018 (0.016)	1.038* (0.021)
Red	0.836*** (0.049)	0.966 (0.032)	1.049 (0.054)	1.004 (0.052)	0.987 (0.049)
2020 ×Red	1.028 (0.068)	1.002 (0.055)	0.981 (0.033)	1.002 (0.036)	1.022 (0.046)
Fixed effects	No	Yes	Yes	Yes	Yes
Observations	2,895,103	2,894,963	717,526	1,050,963	1,379,826
Log Likelihood	-1,748,705	-1,718,952	-408,826.01	-606,959.4	-802,831.63

Notes: This table reports estimates of likelihood of re-enrolling for the following year, graduating, and exam attendance relative to a control period, for individuals under a more stringent COVID-19 policy regime (i.e. red zone) during the first lockdown extension period. For panels A, the sample covers all students enrolled in a university degree in France (excluding Ile-de-France) from 2012 to 2021. For panel B, the sample consists of all students enrolled in a graduation year (excluding Ile-de-France) from 2012 to 2021. Each column presents a logit regression performed separately for a given control group time window. The regression includes university fixed effects (to account for differences in university quality) and the student characteristics listed in Table 1. The dropped observations between columns (1) and (2) of Panel B result from universities where the graduation rate is perfectly predicted. Standard errors (shown in parentheses) are adjusted for clustering at the university level. Asterisks indicate traditional levels of statistical significance (***, **, *, for 0.01, 0.05, 0.1, respectively).

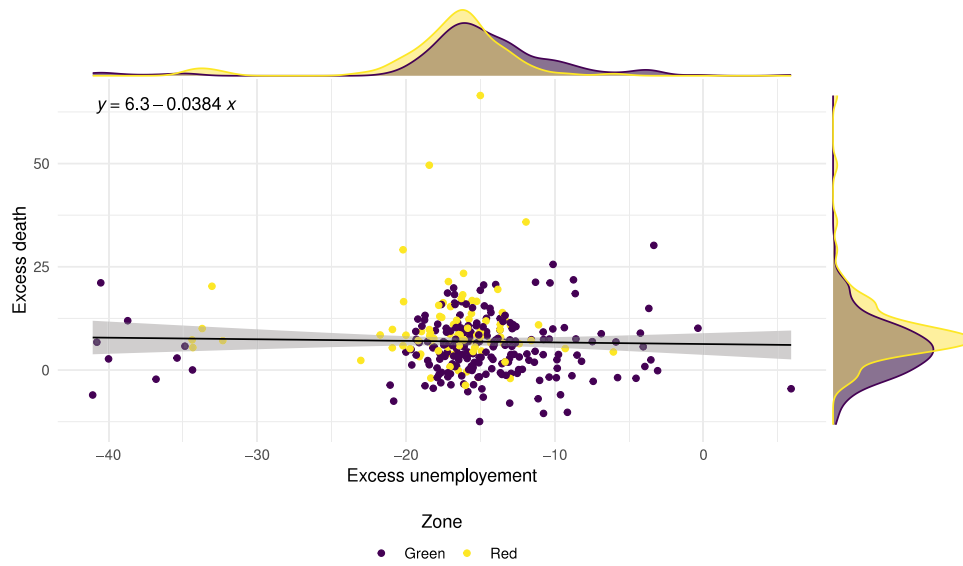


Fig. E.1. Changes in unemployment and mortality.

Notes: The figure portrays the relationship between excess unemployment and excess mortality, as measured at the employment zone level against their 2016 to 2020 baseline rates. Within the panel, each data point represents an observation. The line represents a univariate linear regression on data from all employment zones, along with a 95% confidence interval in gray. The equation for this linear regression is presented in the upper-left quadrant of the plot. The datapoints were then differentiated according to whether the corresponding employment zone was situated in the green or red zones during the second lockdown phase in France in 2020: the red zone is indicated by the darker shade of purple, while the green zone is depicted in the lightest shade of yellow. The distribution of each variable is represented along its respective axis. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

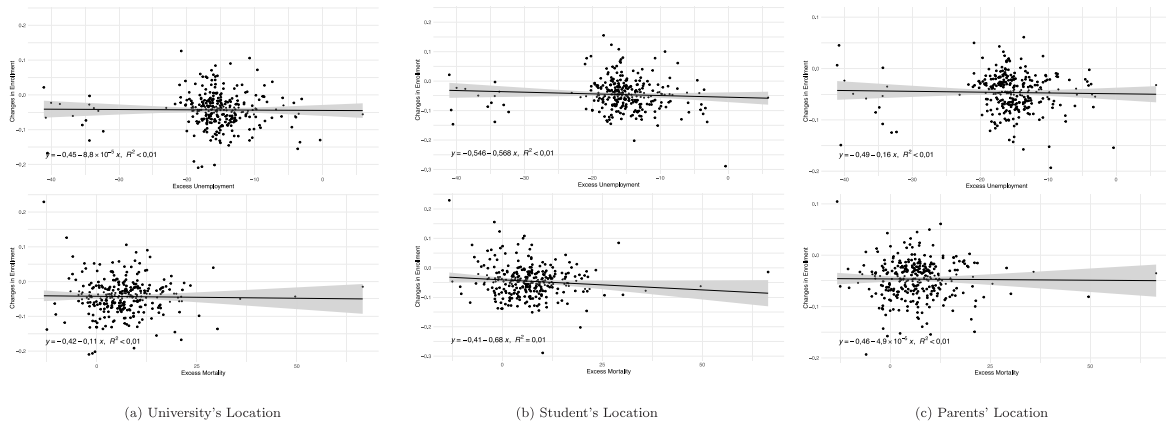


Fig. F.1. Potential mechanisms and enrollment rate.

Notes: The figure illustrates the correlation between students' locations and the two mechanisms of interest. The dependent variable measures the disparity in re-enrollment behaviors between the year affected by the COVID-19 pandemic and the baseline period spanning from 2012 to 2020. The upper panel in each column depicts the connection between this variable and excess unemployment during the pandemic year. All measurements are conducted at the employment zone level. The displayed equation represents a univariate OLS regression. All locations are defined at the employment zone level: (a) the employment zone where the university is situated, (b) that of the reported residence of the student, and (c) that of the reported residence of the student's parents.

Appendix E. Relationship between our two mechanisms

Data availability

See Fig. E.1.

The authors do not have permission to share data.

Appendix F. Potential mechanisms and alternative measure

See Figs. F.1–F.3.

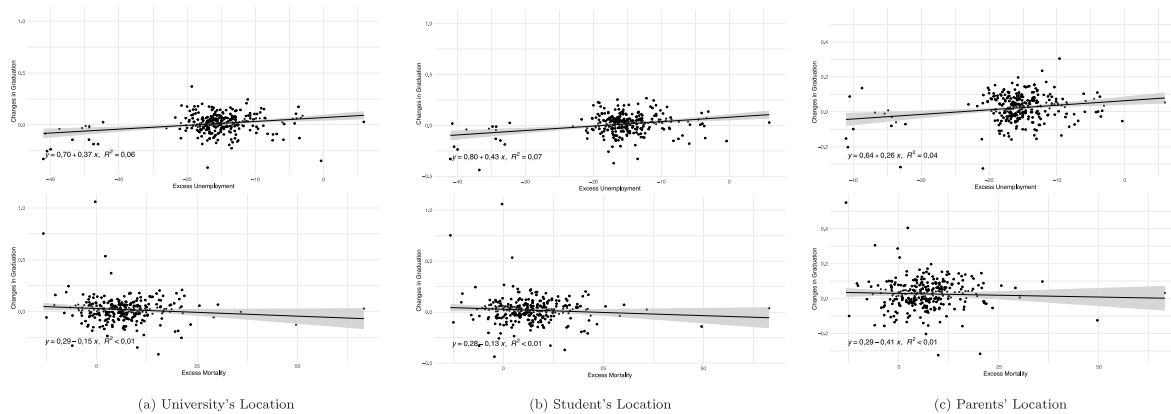


Fig. F.2. Potential mechanisms and graduation rate.

Notes: The figure illustrates the correlation between students' locations and the two mechanisms of interest. The dependent variable measures the disparity in graduation rate between the year affected by the COVID-19 pandemic and the baseline period spanning from 2012 to 2020. The upper panel in each column depicts the connection between this variable and excess unemployment during the pandemic year. All measurements are conducted at the employment zone level. The displayed equation represents a univariate OLS regression. All locations are defined at the employment zone level: (a) the employment zone where the university is situated, (b) that of the reported residence of the student, and (c) that of the reported residence of the student's parents.

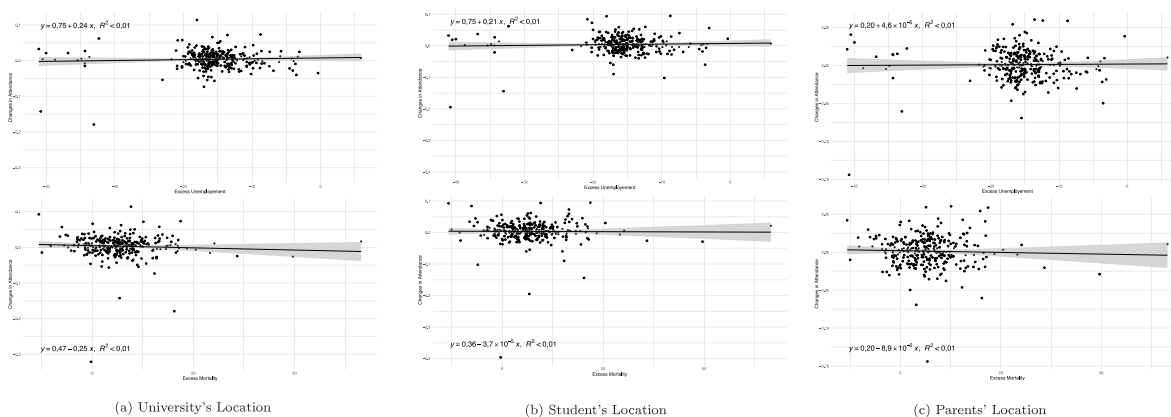


Fig. F.3. Potential mechanisms and attendance rate.

Notes: The figure illustrates the correlation between students' locations and the two mechanisms of interest. The dependent variable measures the disparity in exam attendance rate between the year affected by the COVID-19 pandemic and the baseline period spanning from 2012 to 2020. The upper panel in each column depicts the connection between this variable and excess unemployment during the pandemic year. All measurements are conducted at the employment zone level. The displayed equation represents a univariate OLS regression. All locations are defined at the employment zone level: (a) the employment zone where the university is situated, (b) that of the reported residence of the student, and (c) that of the reported residence of the student's parents.

References

- Aalto, A.-M., Müller, D., & Tilley, J. L. (2023). From epidemic to pandemic: Effects of the COVID-19 outbreak on high school program choices in Sweden. *Labour Economics*, 82, Article 102346.
- Adamopoulos, E., & Tanzi, G. M. (2017). Academic drop-out and the great recession. *Journal of Human Capital*, 11(1), 35–71.
- Agostinelli, F., Doepke, M., Sorrenti, G., & Zilibotti, F. (2022). When the great equalizer shuts down: Schools, peers, and parents in pandemic times. *Journal of Public Economics*, 206, Article 104574.
- Aina, C., Baici, E., Casalone, G., & Pastore, F. (2018). The economics of university dropouts and delayed graduation: a survey. 11421, IZA Discussion Papers.
- Alan, S., & Turkum, B. (2023). *Disruption to schooling impedes the development of abstract reasoning and theory of mind in children: Technical report DP17971*, Paris & London: CEPR Press, CEPR Discussion Paper No. 17971.
- Andrew, A., Cattán, S., Costa Dias, M., Farquharson, C., Kraftman, L., Krutikova, S., et al. (2020). Inequalities in children's experiences of home learning during the COVID-19 lockdown in England. *Fiscal Studies*, 41(3), 653–683.
- Arsandaux, J., Montagni, I., Macalli, M., Texier, N., Pouriél, M., Germain, R., et al. (2021). Mental health condition of college students compared to non-students during COVID-19 lockdown: the CONFINS study. *BMJ open*, 11(8), Article e053231.
- Atkinson, A. B., & Morelli, S. (2011). Economic crises and inequality. (2011/6), UNDP-HDRO occasional papers.
- Aucejo, E. M., French, J., Araya, M. P. U., & Zafar, B. (2020). The impact of COVID-19 on student experiences and expectations: Evidence from a survey. *Journal of Public Economics*, 191, Article 104271.
- Balmford, B., Annan, J. D., Hargreaves, J. C., Altoè, M., & Bateman, I. J. (2020). Cross-country comparisons of COVID-19: Policy, politics and the price of life. *Environmental and Resource Economics*, 76(4), 525–551.
- Becker, G. S. (1964). *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago Press.
- Benveniste, S. (2021). Like father, like child: Social reproduction in the french GrandesEcoles throughout the 20 th century.
- Bethhäuser, B. A., Bach-Mortensen, A. M., & Engzell, P. (2023). A systematic review and meta-analysis of the evidence on learning during the COVID-19 pandemic. *Nature Human Behaviour*, 1–11.
- Blom, E., Cadena, B. C., & Keys, B. J. (2021). Investment over the business cycle: Insights from college major choice. *Journal of Labor Economics*, 39(4), 1043–1082.
- Bonneau, C., Charrouset, P., Grenet, J., & Thebault, G. (2021). Quelle démocratisation des grandes écoles depuis le milieu des années 2000? *Institut des politiques publiques (IPP)*.
- Bonneau, C., & Grobon, S. (2022). Unequal access to higher education based on parental income: evidence from France. *Documents de travail du Centre d'Économie de la Sorbonne*.
- Brandily, P., Brébion, C., Briole, S., & Khoury, L. (2021). A poorly understood disease? The impact of COVID-19 on the income gradient in mortality over the course of the pandemic. *European Economic Review*, 140, Article 103923.
- Bulman, G., & Fairlie, R. W. (2016). Technology and education: Computers, software, and the internet. In *Handbook of the economics of education: vol. 5*, (pp. 239–280). Elsevier.
- Bulman, G., & Fairlie, R. (2022). The Impact of COVID-19 on Community College Enrollment and Student Success: Evidence from California Administrative Data. *Education Finance and Policy*, 1–20.

- Bulman, G., Fairlie, R., Goodman, S., & Isen, A. (2021). Parental resources and college attendance: Evidence from lottery wins. *American Economic Review*, 111(4), 1201–1240.
- CampusFrance (2022). Tuition fees in France. <https://www.campusfrance.org/en/tuition-fees-france>.
- Chan, C. K. Y. (2022). A review of the changes in higher education assessment and grading policy during covid-19. *Assessment & Evaluation in Higher Education*, 1–14.
- Charoussat, P., & Monnet, M. (2022). Gendered teacher feedback, students' math performance and enrollment outcomes: A text mining approach. 19, PSE Working Paper.
- Chen, D. L., Ertac, S., Evgeniou, T., Miao, X., Nadaf, A., & Yilmaz, E. (2022). Grit and academic resilience during the COVID-19 pandemic. 02, INSEAD Working Paper.
- Cunha, J. M., & Miller, T. (2014). Measuring value-added in higher education: Possibilities and limitations in the use of administrative data. *Economics of Education Review*, 42, 64–77.
- Dang, T. H., Nguyen, C. V., Nguyen, O. T. T., & Phung, T. D. (2022). Do positive income shocks benefit children's education? Evidence from Vietnam. *Applied Economics*, 1–25.
- Di Pietro, G. (2018). The academic impact of natural disasters: evidence from L'Aquila earthquake. *Education Economics*, 26(1), 62–77.
- Dincher, M., & Wagner, V. (2021). Teaching in times of COVID-19: determinants of teachers' educational technology use. *Education Economics*, 29(5), 461–470.
- Failache, E., Katzkowicz, N., Parada, C., Querejeta, M., & Rosá, T. (2024). *Gendered impacts of COVID-19 on university enrollment and major choices: Technical report*.
- Ferreira, F. H., & Schady, N. (2009). Aggregate economic shocks, child schooling, and child health. *The World Bank Research Observer*, 24(2), 147–181.
- Ford, T., John, A., & Gunnell, D. (2021). Mental health of children and young people during pandemic. *Bmj*, 372.
- Grenet, J., Grönqvist, H., Hertegård, E., Nybom, M., & Stuhler, J. (2024). How early career choices adjust to economic crises. 03, PSE Working Paper.
- Grewenig, E., Lergetporer, P., Werner, K., Woessmann, L., & Zierow, L. (2021). COVID-19 and educational inequality: How school closures affect low-and high-achieving students. *European Economic Review*, 140, Article 103920.
- Gury, N. (2011). Dropping out of higher education in France: a micro-economic approach using survival analysis. *Education Economics*, 19(1), 51–64.
- Guse, J., Weegen, A. S., Heinen, I., & Bergelt, C. (2021). Mental burden and perception of the study situation among undergraduate students during the COVID-19 pandemic: a cross-sectional study and comparison of dental and medical students. *BMJ Open*, 11(12).
- Issehnane, S., & Moulin, L. (2024). In the eye of the storm: The disrupted career paths of Young people in the wake of COVID-19. *The BE Journal of Economic Analysis & Policy*, 24(2), 565–596.
- Kung, S., Doppen, M., Black, M., Braithwaite, I., Kearns, C., Weatherall, M., et al. (2021). Underestimation of COVID-19 mortality during the pandemic. *ERJ Open Research*, 7(1).
- Lichand, G., Christen, J., & van Egeraat, E. (2023). Behavioral nudges reduced dropout risk among vulnerable students during the pandemic: experimental evidence from Brazil. In *AEA papers and proceedings: vol. 113*, (pp. 494–497). American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.
- Montmarquette, C., Mahseredjian, S., & Houle, R. (2001). The determinants of university dropouts: a bivariate probability model with sample selection. *Economics of Education Review*, 20(5), 475–484.
- Moulin, L., Flacher, D., & Harari-Kermadec, H. (2016). Tuition fees and social segregation: lessons from a natural experiment at the University of Paris 9-Dauphine. *Applied Economics*, 48(40), 3861–3876.
- Parolin, Z., & Lee, E. K. (2021). Large socio-economic, geographic and demographic disparities exist in exposure to school closures. *Nature Human Behaviour*, 5(4), 522–528.
- Rivera, R., Rosenbaum, J. E., & Quispe, W. (2020). Excess mortality in the United States during the first three months of the COVID-19 pandemic. *Epidemiology & Infection*, 148.
- Schanzenbach, D. W., & Turner, S. (2022). Limited supply and lagging enrollment: Production technologies and enrollment changes at community colleges during the pandemic. *Journal of Public Economics*, 212, Article 104703.
- Schueler, B. E., & Miller, L. C. (2023). Post-pandemic onset public school enrollment and mobility: Evidence from Virginia. *Educational Evaluation and Policy Analysis*, Article 01623737231178299.
- Shang, Q., & Lee, L.-f. (2011). Two-step estimation of endogenous and exogenous group effects. *Econometric Reviews*, 30(2), 173–207.
- Silverman, J. D., Hupert, N., & Washburne, A. D. (2020). Using influenza surveillance networks to estimate state-specific prevalence of SARS-CoV-2 in the United States. *Science Translational Medicine*, 12(554), eabc1126.
- Stantcheva, S. (2022). Inequalities in the times of a pandemic. *Economic Policy*, 37(109), 5–41.
- Svaleryd, H., & Vlachos, J. (2022). COVID-19 and school closures. In *Handbook of Labor, Human Resources and Population Economics* (pp. 1–25). Springer.
- Terrier, C., Chen, D. L., & Sutter, M. (2021). COVID-19 within families amplifies the prosociality gap between adolescents of high and low socioeconomic status. *Proceedings of the National Academy of Sciences*, 118(46), Article e2110891118.
- Wachter, T. V. (2020). The persistent effects of initial labor market conditions for young adults and their sources. *Journal of Economic Perspectives*, 34(4), 168–194.
- Werner, K., & Woessmann, L. (2023). The legacy of COVID-19 in education. *Economic Policy*, eiad016.
- Ye, X., Zhai, M., Feng, L., Wang, W., Wu, H., et al. (2022). Still want to be a doctor? Medical student dropout in the era of COVID-19. *Journal of Economic Behavior and Organization*, 195, 122–139.
- Yorifuji, T., Matsumoto, N., & Takao, S. (2021). Excess all-cause mortality during the COVID-19 outbreak in Japan. *Journal of Epidemiology*, 31(1), 90–92.