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Impact of the COVID-19 Pandemic on University New Entry, Enrollment, and Graduation on STEM and Non-STEM Majors in Mexico

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Abstract

Using administrative data on all higher education institutions in Mexico, we estimate the effect of the COVID-19 pandemic on new entry, enrollment, and, graduation outcome. The analysis is conducted by area of study and gender. We explore heterogeneous effects by delivery format, funding source, and elite university status. Finally, we estimate the effect of the pandemic on the gender gap in STEM and non-STEM related majors. Overall, we find that the pandemic's largest effect was on delaying graduation, followed by new entry. The impact on enrollment was small. Public universities were hit the hardest. With the exception of graduation, asynchronous programs did not experience lower impacts. On the other hand, elite universities benefited from the pandemic. Regarding the gender gap in STEM majors, the pandemic reduced the gap on new entry and enrollment outcomes by 24.3% and 7.3%, respectively.

JEL: I21, I23, I25, and O15.
Key words: COVID-19, enrollment, graduation outcomes, STEM, and gender gap.

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1 Introduction

The COVID-19 pandemic has had a profound impact on global education. In addition to representing an income and health shock, the transition to online delivery formats and school closure severely disrupted education UNESCO (2021). Particularly, developing countries, which often have limited technological infrastructure, have been disproportionately affected, with students from lower-income backgrounds facing significant challenges United Nations (2020). Given the magnitude of this impact and the crucial role of education, it is important to comprehensively understand the extent to which the pandemic has affected education and to analyze the differential effects on various institutional characteristics.

This paper presents the first study conducted in a developing country that utilizes administrative data from all higher education institutions to estimate the pandemic's average effects on new entry, enrollment, and graduation outcomes at the institution and area of study levels. Furthermore, this paper examines heterogeneous effects by gender and university characteristics, including delivery format (synchronous vs. asynchronous programs), funding source (public vs. private universities), and elite status (top-20 vs. non-top-20 universities according to the QS ranking for Mexico).

To estimate the effects of the pandemic, a difference-in-difference specification is employed, with the treatment group consisting of all higher education institutions during the academic years 2019-2020 and 2020-2021, and the control group consisting of all higher education institutions during the academic years 2017-2018 and 2018-2019. When analyzing heterogeneous treatment effects, a triple difference-in-difference specification is utilized.

The findings reveal that the largest effect of the pandemic was on graduation outcomes, with an approximate effect of 20%, followed by new entry, with an approximate effect size of 15%, and enrollment, which experienced only slight decreases of around 3% in some areas of study. However, there were differential effects by area of study. Contrary to existing literature findings that suggested larger effects on women

(Idris et al., 2023; Burzynska and Contreras, 2020; Kidman et al., 2022), the results for Mexican higher education institutions indicate the opposite trend. These effects narrowed the gender gap in STEM-related majors in terms of new entry and enrollment, with reductions of 24.3% and 7.3%, respectively. However, in non-STEM-related majors where women are more prevalent than men, the gender gap increased in new entry and graduation by 6.94% and 24.46%, respectively, although it decreased in enrollment by 5.96%. Furthermore, heterogeneous effects were observed based on university characteristics, with asynchronous programs showing limited protection against the shock of the pandemic, public institutions performing worse than private ones in terms of graduation outcomes, and elite institutions experiencing positive effects on new entry for majors related to education, engineering, health, services, and business.

The remainder of the paper is organized as follows. Section 2 describes the related literature and outlines how this study contributes to it. Section 3 presents the data and methods employed. The analysis results are presented in Section 3, along with discussions on robustness checks, heterogeneous effects, and the impact of the pandemic on the STEM gender gap. Section 4 discusses the current study's limitations and identifies areas for further research. Finally, Section 5 concludes.

1.1 Literature Review

The COVID-19 pandemic has been a significant disruptor to the field of education[1], prompting a growing body of literature to emerge to analyze and propose policy responses rapidly. Most studies have focused on the pandemic's impact on students' learning, enrollment, experience, expectations, and education inequality.

Numerous studies have examined the short-term impacts of the pandemic on enrollment, with generally small effects observed. For instance, Bulman et al. (2022) estimate minimal changes in enrollment for 4-year colleges in California, while Chatterji et al. (2021) report decreases of 2% to 3% for high-school students. However,

[1]For studies on other large shocks, as the recent recessions, see Oreopoulos et al. (2012) and Rothstein (2020)

these decreases have persisted even after the return to in-person teaching, as noted by Roy and Nguyen-Hoang (2022). Moreover, the pandemic had a larger effect on enrollment for students from lower-income backgrounds. For example, community colleges in California experienced an 11% decrease in enrollment between 2019 and 2020, followed by an additional 9% decrease the following year (Bulman and Fairlie, 2022). Most of these studies have focused either on specific states or used administrative data of particular schools. We contribute to this literature by providing the first causal estimates of the pandemic's effect on enrollment in Mexico, utilizing data on all higher education institutions in Mexico, and presenting results disaggregated by area of study and gender, which has not been extensively explored[2].

The closure of schools and the shift towards online education during the pandemic have resulted in large learning losses, as reported by Agostinelli et al. (2022), Angrist et al. (2021), Sabates et al. (2021), and Hevia et al. (2022). These losses are expected to have a compounded effect on students' educational trajectories. For example, Roy and Nguyen-Hoang (2022) and Kaffenberger (2021) predict that a loss of approximately three months of learning may lead to a full year of learning loss[3]. Furthermore, these learning losses have disproportionately affected students from low-income backgrounds (Agostinelli et al., 2022). In this last regard, the impact of the pandemic was particularly severe for students with limited access to technological infrastructure, with an estimated 30% of school children globally unable to be reached by remote learning policies (Ardington et al., 2021). The pandemic has further exacerbated pre-existing vulnerabilities to educational disadvantages (Jones et al., 2021; Akabayashi et al., 2023). Consistent with the prediction that the pandemic would widen educational gaps by income level, Aucejo et al. (2020) and Rodríguez-Planas (2022) find that it dis-proportionally impacted the graduation plans of low-income students. We complement this literature by providing insights into the heterogeneous

[2] On a companion paper, Balmori de la Miyar et al. (forthcoming) study the pandemic's effect on enrollment and graduation outcomes, but only focus on business majors and do not present results by gender.

[3] Although some studies, as Moscoviz and Evans (2022) and Sartling-Alves et al. (2023), have contested the magnitude of these losses.

effects of the pandemic on graduation outcomes, depending on the university's source of funding, and on whether the university is considered an elite institution. As with the results we report on enrollment, we use data at the level of area of study for each higher education institution in Mexico.

Finally, while there have been notable exceptions (Idris et al., 2023; Burzynska and Contreras, 2020; Kidman et al., 2022), there has not been much emphasis on the pandemic's differential effect by gender and area of study. We contribute to bridging this gap in the literature by analyzing the pandemic's effect on the gender gap in STEM and non-STEM related majors in new entry, enrollment, and graduation outcomes.

2 Data and Methods

2.1 Data

We use administrative data on new entry, enrollment, and graduation outcomes of all higher education institutions in Mexico. The data is collected and reported by the National Association of Universities and Institutions of Higher Education (ANUIES) at the program level for each institution, spanning the years 2010 to 2021. The dataset includes information on the delivery format of the programs (synchronous or asynchronous), the funding source of the universities (public or private), and the elite status of the schools (top 20 universities in Mexico according to the QS Ranking). This study's analysis is limited to four academic years, specifically from 2018-2019 to 2020-2021. ANUIES classifies programs into ten areas of study: sciences, health, engineering, information technology, social sciences, education, business, arts and humanities, agronomy and veterinary, and services. We study the pandemic's effect on each area of study.

Summary statistics are presented in Table 1 for the three outcomes of interest, separately for each of the ten areas of study mentioned above, both pre-and post-Covid-19. For example, prior to the pandemic, an average of 154.25 students enrolled in a health-related program in a given year. Notably, following the pandemic, there was a decrease in new entry, enrollment, and graduation outcomes for all areas of study, except for sciences in new entry and enrollment and for education, information technology, and arts and humanities in enrollment.

2.2 Methods

Difference-in-differences We employ a difference-in-differences (DD) methodology to estimate the impacts of the COVID-19 pandemic on new entry, enrollment, and graduation of students in higher education institutions. The main DD specification used in our analysis is as follows:

$$Y_{icmy} = \alpha + \gamma Treatment_{imy} + \delta Post_{imy} + \beta(Post \times Treament)_{imy} + \delta X_{imy} + e_{icmy}, \qquad (1)$$

where Y_{imy} represents the outcome of interest for higher education institution i, campus c, in area of study m, and year y. $Treatment_{imy}$ denotes a dummy variable equal to one for treated institutions, which refers to higher education institutions during the academic years 2019-2020 and 2020-2021, and zero for the control institutions, which refers to higher education institutions during the academic years 2017-2018 and 2018-2019. The variable $Post_{imy}$ denotes a dummy variable equal to one for the period post-treatment (academic years 2018-2019 and 2020-2021), and zero otherwise (academic years 2017-2018 and 2019-2020). The average treatment effect on the treated is estimated by the parameter β. Lastly, X_{imy} denotes a set of controls, which includes whether the program is synchronous, whether the university is public, and whether the university is among the top 20 universities according to the QS-rankings.

Difference-in-differences-in-differences To study heterogeneous effects by university characteristics, we estimate a difference-in-difference-in-difference (DDD) methodology. We investigate heterogeneous effects by different formats of course delivery (synchronous vs. asynchronous classes), source of funding (public vs. private university), and elite status (top20 vs. non-top20 universities). Our DDD specification is as follows:

$$
\begin{aligned}
Y_{icmy} =& \alpha + \beta_1 Treatment_{imy} + \beta_2 Het_{icy} + \beta_3 Post_{my} + \beta_4 (Post \times Treatment)_{imy} + \\
& \beta_5 (Treatment \times Het)_{icmy} + \beta_6 (Het \times Post)_{icmy} + \\
& \beta_7 (Post \times Treatment \times Het)_{icmy} + e_{icmy},
\end{aligned} \tag{2}
$$

where both $Treament_{imy}$ and $Post_{my}$ are specified as above, and Het_{icy} denotes a dummy variable equal to one if the institution belongs to a specific heterogeneous sub-group in consideration, and zero otherwise.

3 Results

The following section presents the results obtained from the DD specification of equation (1), starting with describing the outcomes of interest, namely new entry, enrollment, and graduation, separately, by area of study. Additionally, we provide DD results by gender and further examine the heterogeneous effects by three program characteristics: format delivery (synchronous vs. asynchronous programs), source of funding (public vs. private universities), and elite status (top20 vs. non-top20 universities). Finally, we present estimates of the impact of the pandemic on the gender gap in STEM and non-STEM outcomes of new entry, enrollment, and graduation.

Table 2 displays the DD results by area of study. For instance, in the sciences, we observe that the pandemic resulted in 16.489 fewer students graduating from science-related majors. This effect is substantial, accounting for approximately 37.5 percent relative to the pre-COVID19 mean. To provide a summary of the results in Table 2, we present in Table 3 the relative effects of the pandemic compared to the pre-COVID19 means, only displaying results that are statistically significant at least at the 10% level.

Each cell in Table 3 represents a DD estimate[4]. Graduation rates were significantly impacted by the pandemic, with declines ranging from 11.6% in arts and humanities

[4]For detailed information on the estimates, please refer to Table 2.

to 37% in the sciences. Social sciences, engineering, health, information technology, business, agronomy and service-related majors experienced an average decline of 22% in the number of students graduating compared to their pre-COVID19 average[5]. These results are consistent with Rodríguez-Planas (2022), who reports that close to 30% of urban college students modified their graduation plans due to the pandemic.

In terms of new entry, the pandemic had the greatest impact on education-related majors, with a decline of 25% compared to pre-pandemic levels. Social sciences and services were also affected, experiencing declines of 18% and 24%, respectively, while the rest of the majors saw declines of approximately 12.5%. On the other hand, sciences fared relatively better regarding new entrants, with no significant effects observed due to the pandemic. As an outcome, enrollment was impacted the least, with null effects observed in the sciences, education, information technology, and arts and humanities majors and declines of around 3.5% for social sciences, engineering, health, agronomy, and services-related majors[6]. However, the low effects on enrollment do not necessarily imply no effects on dropout behavior.

Overall, the pandemic significantly impacted graduation rates and new entry, with relatively low average enrollment effects. The decline in graduation rates may be attributed to students taking fewer classes during the pandemic, resulting in delayed graduation, or students completing their classes but facing delays in processing the paperwork required for graduation. The substantial effect of 25% on new entry in education-related majors is concerning, as it may have implications for future teachers shortages if the effect persists or is not reversed. Future research should investigate the duration of this effect and whether the pandemic has caused a permanent shift in students' preferences, dissuading them from pursuing majors related to education. More generally, it is important to understand the prevalence and sources of these change in preferences due to the pandemic. As Aucejo et al. (2020) reported, approximately 12%

[5] For a focus on business majors see Balmori de la Miyar et al. (forthcoming). The majors grouping for the business area of study has been slightly revised in this study compared to Balmori de la Miyar et al. (forthcoming).

[6] These results are similar to those found by Bulman and Fairlie (2022) and Bird et al. (2022).

of students considered changing majors due to the pandemic.

Table 4 displays the same analysis results as Table 3, but with a breakdown by gender. This table is again a summary of the DD estimates. For details on the estimations by area of study, refer to Tables A.1 to A.10 in the Appendix. The data reveals that, on the whole, men have been more adversely impacted by the pandemic in terms of new entry and enrollment across various fields of study, with declines ranging from two to four percentage points. The only exception in our analysis, where female were impacted significantly more, was for majors related to information technology, where no significant effect was observed for men. However, a 4.25% decrease was observed for women[7]. A significant reversal in the direction of the effect was observed in the context of graduation, with female students experiencing a larger overall impact from the pandemic. The pandemic's higher effect on graduation outcomes for women is consistent with Kidman et al. (2022), who found that fewer older female students returned to school after the pandemic. Burzynska and Contreras (2020) argue that female students, especially in developing countries, may be in danger of higher drop-out rates due to pregnancy or higher responsibilities in household chores due to the pandemic, which may discourage school completion. Future studies should analyze whether this effect was temporal, if the pandemic only delayed graduation, or if other factors were considered to understand this gender gap.

3.1 Robustness Checks

We conduct two robustness analyses to ascertain the validity of our estimates. First, we conducted a placebo test to gather evidence favoring the parallel trends assumption. Assuming that the pandemic hit Mexico in 2019 rather than 2020, we should find no effects. We redefine $Treatment_{imy}$ as equal to one for higher education institutions

[7]It should be noted that there were no parallel pre-trends identified when looking at enrollment in education majors and arts and humanities both for men and women, and agronomy for men. Regarding new entry, we do not find pre-parallel trends in engineering majors for women, and in arts and humanities and services. The results for these specific areas of study and outcomes should be interpreted with caution. For a full description of a placebo test for pre-parallel trends, refer to Table A.22 in the Appendix

from academic years 2018-2019 and 2019-2020, and equal to zero for institutions during the academic years 2016-2017 and 2017-2018. Likewise, the $Post_{imy}$ was redefined to be equal to one for 2019-2020 and 2017-2018, and zero for 2018-2019 and 2016-2017. The results are found in Table A.21 for the general DD results, and in Table A.22 when estimating the DD by gender. As expected, the DD effects were generally insignificant, except for enrollment effects in education, agronomy, and arts and humanities-related majors and new entry effects in engineering, arts and humanities, and services majors, which showed significant differences. This indicates that for these specific areas of study and outcomes, the parallel trends assumption may not hold. For all the other areas of study and outcomes, we find parallel pre-trends between the treatment and control group, which we take as suggestive evidence that the parallel trends assumption holds.

Secondly, we conducted a correction for multiple hypothesis testing because of the large number of estimations resulting from the ten areas of study and three outcomes of interest. We used False Discovery Rate q-values as suggested by Anderson (2008). The results for the main DD specification are presented in Table A.23, and for the analysis conducted separately by gender in Table A.24. We report in parenthesis the p-values, and the q-values in brackets below them. None of the statistically significant results become insignificant when adjusting the p-values for multiple hypothesis testing, which is particularly important in our analysis to ensure the reliability of our findings given the large number of estimations conducted.

3.2 Heterogeneous Effects

Following the specification outlined in equation 2, the results of the difference-in-difference-in-difference (DDD) estimates, categorized by area of study, can be found in Table A.11 to Table A.20 in the appendix. These tables provide insights into the heterogeneous effects of different university characteristics, namely format of delivery, source of funding, and elite status. A summary of these results is presented in Table 5.

The results can be interpreted as follows. For instance, in science majors, as shown in Panel A of Table A.11 in the Appendix, we observe that among treated institutions, synchronous programs experienced a decrease in enrollment of 49.1 students compared to asynchronous programs in the treatment group. This differential effect represents 10.96% of the pre-COVID19 enrollment mean of synchronous majors in the sciences. This 10.96% is reported in the first row of Table 5. Hence, the reported results provide an indication of the magnitude of the heterogeneous effect relative to the pre-pandemic levels of the sub-group under consideration.

Table 5 further reveals that public universities performed worse than private universities in terms of graduation and for all areas of study. The magnitude of the heterogeneous effect ranged from 20.37% for majors related to health studies to 40.72% in business majors. In terms of synchronous programs, a negative treatment effect was observed compared to asynchronous programs in enrollment for the sciences and engineering. This decline may be attributed to the importance of in-person training in these areas of study, particularly in laboratories. Furthermore, for majors related to engineering, information technology, and services, synchronous programs exhibited lower graduation outcomes compared to asynchronous programs. Nevertheless, the relative null differential effects for synchronous programs on new entry and enrollment are consistent with Bulman and Fairlie (2022), who found that having a large online presence before the pandemic did not protect schools. We find similar results except for graduation outcomes.

Interestingly, the pandemic benefited the top-20 universities compared to the non-top20 universities, for majors related to education, engineering, health, business, and services. The positive effect was observed in new entries and, to a lesser extent, in enrollment. This may suggest that students anticipated the challenges that schools would face due to the pandemic and changed their preferences in favor of schools with greater resources to respond effectively to the crisis. Although some of our top schools are public and have low tuition, the best schools tend to attract students with higher incomes and resources. In this regard, the differential effects we find here are consistent with the findings in the literature that the pandemic disproportionately impacted lower income-students.

3.3 STEM Gender Gap

In this section, we analyze the impact of the COVID-19 pandemic on the STEM gender gap in new entry, enrollment, and graduation outcomes. Specifically grouping the programs into STEM-related and non-STEM-related fields. For this study, we define STEM-related areas of study as including sciences, health, engineering, and information technology majors. In contrast, non-STEM areas of study encompass business, arts and humanities, social sciences, education, agronomy and veterinary, and services majors. Descriptive statistics of pre- and post-COVID19 periods for both groups are presented in the Appendix in Table A.25.

To estimate the effect of the pandemic on the STEM gender gap in outcomes of interest, we employ a difference-in-differences (DD) approach, specified as follows:

$$Y^M_{icmy} - Y^F_{icmy} = \alpha + \gamma Treatment_{imy} + \delta Post_{imy} + \beta(Post \times Treament)_{imy} + \delta X_{imy} + e_{icmy}, \tag{3}$$

where Y^M_{icmy} and Y^F_{icmy} denote the outcome of interest for male and female students respectively, of institution i, campus c, in area of study m, and in year y. The rest of the variables are specified as in our main DD specification. The results for both STEM and non-STEM areas of study are presented in Table 6. To validate the results, we conducted a placebo test simulating that the pandemic occurred in 2019 instead of 2020. As observed in Table A.26 in the Appendix, we found no statistically significant effects, which supports the assumption of parallel trends between the treatment and control group.

Prior to the pandemic, the average gender gap in STEM-related majors was 26.51, with more men than women entering these fields. However, this gap decreased by 6.44 students due to the pandemic, representing a reduction of 24.3% from the pre-pandemic mean, a large effect. Similarly, we observed a reduction in the gender gap in enrollment in STEM-related areas of study by 7.3%. The pandemic affected both men and women, as we can see in Table 4, but the pandemic decreased the gender gap because, at least in Mexico, it impacted men the most.

In contrast, for non-STEM areas of study, the pre-COVID-19 mean of the gender gap was negative, indicating a higher representation of women in these fields. Interestingly, due to the pandemic, the gender gap in new entry and graduation decreased by 6.94% and 24.46%, respectively. However, the gender gap in enrollment increased by 5.96%, indicating that even fewer men were enrolled in non-STEM majors.

4 Discussion

This study aims to estimate the short-term effects of the COVID-19 pandemic on education outcomes. However, it is also crucial to investigate its long-term effects and determine whether the changes brought by the pandemic will persist. For instance, the extensive use of online educational tools during school closures may result in a permanent shift towards increasing technology use in the classroom, even as the pandemic impacted both synchronous and asynchronous programs. Therefore, assessing the long-term effects of the pandemic is a primary consideration for future research.

Whereas we leverage high-quality administrative data on new entry, enrollment, and graduation outcomes, a shortcoming of this study is the lack of data on learning and student demographic characteristics besides gender. So far, studies in developing countries focusing on learning generally use administrative data on a certain school[8]. A more general study is needed for various levels of education. Furthermore, although we do explore heterogeneous effects by university characteristics; more student demographic data would be welcomed.

Finally, while most of the literature on the pandemic's impact on education has

[8] An exception for the case of Mexico is Roy and Nguyen-Hoang (2022)

focused on student learning and outcomes, few studies have examined its effects on teachers[9]. This is especially critical in Mexico, given the significant effects found in new entry for majors related to education. If these effects persist, there may be a shortage of professors in an already inadequate educational system. Thus, policies that support and retain good professors will be necessary, and the current policy awareness momentum can be an opportunity to implement much-needed reforms. Detailed policy recommendations to cope with the pandemic can be found in prior works, such as World Bank (2020) and World Bank (2021), but the question remains on how we re-build better the education systems after the pandemic.

5 Conclusion

In this study, we leverage high quality-data on all higher education institutions in Mexico to study the pandemic's impact on new entry, enrollment, and graduation outcomes. Using a difference-in-difference specification, we estimate the pandemics' effect by area of study and gender, and we further complement this analysis by studying heterogeneous effects based on three university characteristics: delivery format, source of income, and elite status.

Overall, our findings indicate that the pandemic had the largest impact on graduation, followed by new entry, and that the effect on enrollment was not large. However, we observe heterogeneous effects by area of study and university characteristics. Specifically, public institutions experienced more adverse outcomes in terms of graduation. Asynchronous programs did not exhibit a particular advantage over synchronous ones, as both programs were equally affected by the pandemic. Moreover, elite institutions appeared to fare better, particularly in terms of new entry, as they may have attracted students who preferred institutions with greater resources to cope with the shock of the pandemic.

Furthermore, we examine the effect of the pandemic on the gender gap in STEM

[9] Dincher and Wagner (2021) is an exception

and non-STEM related majors. Our findings reveal that in STEM majors, the pandemic decreased the gender gap in new entry and enrollment by 24.3% and 7.3%, respectively. Both men and women felt the impact of the pandemic, but the gender gap decreased because men were disproportionately affected. Conversely, in non-STEM majors, where there is a larger population of women compared to men, the gender gap increased in new entry and graduation by 6.94% and 24.46%, respectively. However, the gender gap decreased in enrollment by 5.96%.

It is important to note that the effects presented in this study are short-term. Future research should investigate whether these effects are reversed or if permanent shifts are observed. Furthermore, given the differential effects of the pandemic on new entry by area of study, it is important to understand whether the pandemic has influenced students' preferences for certain areas of study. Of particular interest is the decline in new entry in education-related majors, as this trend, if not reversed, may result in shortages in teaching positions.

6 Figures and Tables

Table 1: Descriptive Statistics

	Health		Sciences		Soc. Sciences		Education		Engineering		Information Tech.	
	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Pre-COVID 19												
New entry	154.25	292.90	112.24	243.32	84.74	250.28	47.15	85.86	137.04	282.94	43.91	127.64
Enrollment	622.83	1,364.34	449.18	991.36	318.56	1,067.43	142.96	269.09	595.90	1,439.01	173.25	500.66
Graduation	69.63	188.33	43.89	110.04	36.12	116.10	21.80	52.07	60.46	150.61	18.68	48.77
N	2,433		786		7,257		4,027		4,429		4,089	
Post-COVID 19												
New entry	135.12	266.98	115.50	260.98	70.85	249.08	42.69	80.62	122.65	292.93	42.28	126.69
Enrollment	599.43	1,354.79	473.63	1,066.64	296.97	1,092.06	147.55	284.15	576.89	1,514.93	176.52	583.90
Graduation	63.37	173.33	37.80	96.11	27.71	103.49	14.55	34.71	52.33	152.07	13.99	37.53
N	897		272		2,683		1,539		1,589		1,399	

	Business		Agronomy & Veterinary		Arts & Humanities		Services	
	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
Pre-COVID 19								
New entry	89.93	266.59	94.00	136.97	45.41	98.19	42.33	97.46
Enrollment	338.20	976.60	373.30	588.02	165.57	431.13	147.74	315.56
Graduation	36.19	101.98	34.14	69.52	14.66	36.97	15.42	32.29
N	8,082		845		2,976		2,221	
Post-COVID 19								
New entry	78.18	260.19	85.58	137.11	42.88	98.14	35.82	73.09
Enrollment	328.53	1,129.86	368.71	601.13	166.43	431.94	139.65	339.77
Graduation	28.74	90.13	27.12	52.87	12.60	41.15	11.57	23.47
N	2,962		299		1,068		817	

Source: ANUIES.
Note: the unit of observation is the number of students per university and area of study. For example, previous to the pandemic, programs in health related studies received on average 154.25 new students each year.

Table 2: Difference-in-difference results

	(1) New entry	(2) Enrollment	(3) Graduation
Sciences			
Post x Treatment	-6.730	7.626	-16.489**
	(4.807)	(6.403)	(8.224)
R^2	0.10	0.13	0.09
Observations	1,058	1,058	1,058
Pre-COVID19 Mean Dep.	112.243	449.182	43.893
Effect as % of Pre-COVID19 Mean	5.99%	1.69%	37.5%
Social Sciences			
Post x Treatment	-15.259***	-10.763**	-8.633***
	(1.881)	(5.114)	(1.779)
R^2	0.12	0.14	0.12
Observations	9,940	9,940	9,940
Pre-COVID19 Mean Dep.	84.739	318.561	36.121
Effect as % of Pre-COVID19 Mean	18%	3.37%	23.9%
Education			
Post x Treatment	-11.906***	0.981	-3.025**
	(2.057)	(3.191)	(1.506)
R^2	0.13	0.17	0.10
Observations	5,566	5,566	5,566
Pre-COVID19 Mean Dep.	47.152	142.964	21.797
Effect as % of Pre-COVID19 Mean	25.25%	0.06%	13.87%
Engineering			
Post x Treatment	-18.442***	-18.173***	-13.365***
	(2.167)	(4.073)	(2.592)
R^2	0.13	0.14	0.12
Observations	6,018	6,018	6,018
Pre-COVID19 Mean Dep.	137.044	595.903	60.460
Effect as % of Pre-COVID19 Mean	13.45%	3.04%	22.1%
Health			
Post x Treatment	-18.865***	-15.386*	-16.937***
	(4.580)	(8.874)	(4.675)
R^2	0.09	0.15	0.13
Observations	3,330	3,330	3,330
Pre-COVID19 Mean Dep.	154.254	622.831	69.626
Effect as % of Pre-COVID19 Mean	12.22%	2.47%	24.32%
Information Technology			
Post x Treatment	-5.282***	1.841	-3.755***
	(1.752)	(2.668)	(1.368)
R^2	0.08	0.11	0.12
Observations	5,488	5,488	5,488
Pre-COVID19 Mean Dep.	43.914	173.252	18.684

Effect as % of Pre-COVID19 Mean	12.02%	1.06%	20.09%
Business			
Post x Treatment	-16.147***	-11.482*	-6.841***
	(3.690)	(6.553)	(1.710)
R^2	0.06	0.09	0.11
Observations	11,044	11,044	11,044
Pre-COVID19 Mean Dep.	89.932	338.202	36.193
Effect as % of Pre-COVID19 Mean	17.95%	3.39%	18.90%
Agronomy & Veterinary			
Post x Treatment	-8.771**	-15.367***	-9.341**
	(3.630)	(4.823)	(3.785)
R^2	0.05	0.09	0.06
Observations	1,144	1,144	1,144
Pre-COVID19 Mean Dep.	94.000	373.304	34.138
Effect as % of Pre-COVID19 Mean	9.33%	4.11%	27.35%
Arts & Humanities			
Post x Treatment	-6.070***	-1.817	-1.710**
	(1.454)	(1.722)	(0.842)
R^2	0.25	0.28	0.20
Observations	4,044	4,044	4,044
Pre-COVID19 Mean Dep.	45.408	165.574	14.656
Effect as % of Pre-COVID19 Mean	13.35%	10.97%	11.67%
Services			
Post x Treatment	-10.391***	-5.442*	-3.428***
	(2.542)	(2.807)	(0.911)
R^2	0.07	0.14	0.12
Observations	3,038	3,038	3,038
Pre-COVID19 Mean Dep.	42.328	147.743	15.416
Effect as % of Pre-COVID19 Mean	24.54%	3.65%	22.23%

Source: ANUIES.

Note: Standard errors in parentheses. * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$)

Table 3: Difference-in-difference results: summary effect as % of Pre-Covid19 mean

	(1) New entry	(2) Enrollment	(3) Graduation
Effect as % of Pre-COVID19 Mean			
Sciences	-	-	-37.5%
Social Sciences	-18%	-3.37%	-23.9%
Education	-25.25%	-	-13.87%
Engineering	-13.45%	-3.04%	-22.1%
Health	-12.22%	-2.47%	-24.32%
Information Technology	-12.02%	-	-20.09%
Business	-17.95%	-3.39%	-18.9%
Agronomy & Veterinary	-9.33%	-4.11%	-27.35%
Arts & Humanities	-13.35%	-	-11.67%
Services	-24.54%	-3.65%	-22.23%

Source: ANUIES.
Note: each cell corresponds to a difference-in-difference (DD) result, for a specific area of study. We only present the estimates that are significant at least at the 10% level. "-" denotes non-significant results. The number of observations used for the DD estimations for the different areas of study are: 1,058 , 9,940 , 5,566 , 6,018 , 3,330, 5,488, 11,044 , 1,144, 4,044, and 3,038.

Table 4: Difference-in-difference results by gender: summary by areas of study, effects relative to Pre-COVID mean

	(1) New entry (Men)	(2) Enrollment (Men)	(3) Graduation (Men)	(4) New entry (Women)	(5) Enrollment (Women)	(6) Graduation (Women)
Effect as % of Pre-COVID19 Mean						
Sciences	-	-	-34.77%	-	-	-39.87%
Social Sciences	-20.07%	-4.68%	-21.02%	-16.57%	-	-25.66%
Education	-26.95%	-	-	-24.65%	-	-14.09%
Engineering	-14.85%	-3.77%	-22.1%	-10.2%	-1.35%	-22.1%
Health	-13.5%	-2.62%	-24.35%	-11.67%	-	-24.31%
Information Technology	-12.85%	-	-21.69%	-9.31%	-4.25%	-16.18%
Business	-19.87%	-4.51%	-17.46%	-16.37%	-	-19.85%
Agronomy & Veterinary	-12.99%	-6.04%	-27.29%	-	-	-27.47%
Arts & Humanities	-16.14%	-2.78%	-13.49%	-11.15%	-	-10.47%
Services	-29.03%	-4.88%	-21.92%	-19.83%	-	-22.49%
Control	Yes	Yes	Yes	Yes	Yes	Yes

Source: ANUIES.
Note: each cell corresponds to a difference-in-difference (DD) result, for a specific area of study and gender group. We only present the estimates that are significant at least at the 10% level. "-" denotes non-significant results. The number of observations used for the DD estimations for the different areas of study are: 1,058 , 9,940 , 5,566 , 6,018 , 3,330 , 5,488, 11,044 , 1,144, 4,044, and 3,038.

Table 5: Heterogeneous treatment effects (DDD): summary by area of study - relative effects as % of Pre-COVID19 mean for heterogeneous group = 1

	(1) New entry	(2) Enrollment	(3) Graduation
Sciences			
Synchronous	-	-10.96%	-
Public	-	-	-37.62%
Top-20	-	-	-
Social Sciences			
Synchronous	-	-	-13.75%
Public	-	-	-35.24%
Top-20	-	-	-
Education			
Synchronous	-	-	-
Public	-	8.9%	-30.98%
Top-20	23.2%	-	-
Engineering			
Synchronous	-	-3.1%	-16.61%
Public	-	-	-26.14%
Top-20	5.75%	2.99%	-
Health			
Synchronous	-	-	-
Public	-	-	-20.37%
Top-20	9.04%	3.13%	-
Information Technology			
Synchronous	-	-	-16.58%
Public	-	-	-27.19%
Top-20	-	-	-
Business			
Synchronous	-	-	-14.01%
Public	-	-	-26.45%
Top-20	17.71%	3.56%	-
Agronomy & Veterinary			
Synchronous	-	-	-
Public	-	-	-40.72%

Top-20	-	-	-
Arts & Humanities			
Synchronous	-	-	-
Public	-	-	-25.19%
Top-20	-	-	-
Services			
Synchronous	-	-	-27.49%
Public	-	-	-26.44%
Top-20	12.48%	8.34%	-

Source: ANUIES.

Note: each cell corresponds to a difference-in-difference-in-difference (DDD) result, for a specific area of study and heterogeneous group. For example, for the *Sciences*, the heterogenous effect in synchronous programs compared to asynchronous programs represented a decrease of 10.96% in enrollment of the pre-pandemic mean of synchronous programs in the treatment group. We only present the estimates that are significant at least at the 10% level. "-" denotes non-significant results. The number of observations used for the DD estimations for the different areas of study are: 1,058 , 9,940 , 5,566 , 6,018 , 3,330 , 5,488, 11,044 , 1,144, 4,044, and 3,038.

Table 6: Difference-in-difference results: STEM and non-STEM Gender Gap

	(1) New entry	(2) Enrollment	(3) Graduation
STEM Gender Gap			
Post x Treatment	-6.446***	-9.093***	-2.071
	(1.308)	(2.942)	(1.259)
Post	0.745	-2.729	-0.773
	(0.936)	(1.716)	(0.923)
Treatment	-1.039	-13.857***	-1.019
	(0.899)	(2.706)	(0.778)
Controls	Yes	Yes	Yes
R^2	0.06	0.05	0.03
Observations	9,834	9,834	9,834
Pre-COVID19 Mean Dep.	26.519	124.612	10.106
Effect as % of Pre-COVID19 Mean	24.30%	7.30%	20.49%
Non-STEM Gender Gap			
Post x Treatment	1.511*	-4.955***	3.368***
	(0.802)	(1.287)	(0.712)
Post	-1.908***	-4.863***	-0.368
	(0.558)	(1.034)	(0.574)
Treatment	-2.990***	-7.468***	-0.354
	(0.695)	(1.524)	(0.514)
Control	Yes	Yes	Yes
R^2	0.05	0.07	0.07
Observations	17,044	17,044	17,044
Pre-COVID19 Mean Dep.	-21.757	-83.151	-13.770
Effect as % of Pre-COVID19 Mean	6.94%	5.96%	24.46%

Source: ANUIES.

Note: Standard errors in parentheses. * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$)

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A Appendix

Table A.1: Difference-in-difference results by gender: sciences

	(1) New entry (Men)	(2) Enrollment (Men)	(3) Graduation (Men)	(4) New entry (Women)	(5) Enrollment (Women)	(6) Graduation (Women)
Post x Treatment	-3.980	2.135	-6.909**	-2.750	5.491	-9.580*
	(2.637)	(3.321)	(3.043)	(2.509)	(3.482)	(5.367)
Post	4.770	7.019*	4.280	4.467	7.556**	7.054
	(3.774)	(3.969)	(3.094)	(2.709)	(3.534)	(5.241)
Treatment	3.317*	8.061	2.487	4.477**	13.619**	3.007
	(1.758)	(6.533)	(2.330)	(1.892)	(5.990)	(2.336)
Control	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.09	0.12	0.10	0.10	0.13	0.08
Observations	1,058	1,058	1,058	1,058	1,058	1,058
Pre-COVID19 Mean Dep.	56.753	224.877	19.866	55.490	224.305	24.027
Effect as % of Pre-COVID19 Mean	7.01%	0.09%	34.77%	4.95%	2.44%	39.87%

Source: ANUIES.
Standard errors in parentheses. * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$)

Table A.2: Difference-in-difference results by gender: social sciences

	(1) New entry (Men)	(2) Enrollment (Men)	(3) Graduation (Men)	(4) New entry (Women)	(5) Enrollment (Women)	(6) Graduation (Women)
Post x Treatment	-6.971***	-6.080***	-2.884***	-8.288***	-4.683	-5.749***
	(0.827)	(2.326)	(0.677)	(1.111)	(2.850)	(1.145)
Post	1.316*	-0.583	0.602	1.968**	1.224	1.197
	(0.754)	(1.332)	(0.647)	(0.942)	(1.726)	(1.001)
Treatment	-0.314	-5.351	-0.520	0.440	-3.966	0.168
	(0.719)	(3.555)	(0.652)	(1.040)	(4.652)	(1.055)
Control	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.11	0.13	0.11	0.12	0.15	0.12
Observations	9,940	9,940	9,940	9,940	9,940	9,940
Pre-COVID19 Mean Dep.	34.720	129.765	13.718	50.019	188.796	22.403
Effect as % of Pre-COVID19 Mean	20.07%	4.68%	21.02%	16.57%	2.48%	25.66%

Source: ANUIES.
Standard errors in parentheses. * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$)

Table A.3: Difference-in-difference results by gender: education

	(1) New entry (Men)	(2) Enrollment (Men)	(3) Graduation (Men)	(4) New entry (Women)	(5) Enrollment (Women)	(6) Graduation (Women)
Post x Treatment	-3.284***	-0.414	-0.709	-8.623***	1.395	-2.316**
	(0.719)	(1.009)	(0.442)	(1.451)	(2.384)	(1.149)
Post	1.378**	0.707	-0.447	3.178***	2.768*	-1.292
	(0.536)	(0.822)	(0.306)	(1.019)	(1.645)	(0.809)
Treatment	2.089***	2.046	-1.236***	6.334***	5.587*	-2.908***
	(0.559)	(1.397)	(0.372)	(1.420)	(3.051)	(1.015)
Control	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.09	0.13	0.09	0.12	0.17	0.09
Observations	5,566	5,566	5,566	5,566	5,566	5,566
Pre-COVID19 Mean Dep.	12.181	35.673	5.365	34.972	107.291	16.432
Effect as % of Pre-COVID19 Mean	26.95%	1.15%	13.21%	24.65%	1.29%	14.09%

Source: ANUIES.
Standard errors in parentheses. * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$)

Table A.4: Difference-in-difference results by gender: engineering

	(1) New entry (Men)	(2) Enrollment (Men)	(3) Graduation (Men)	(4) New entry (Women)	(5) Enrollment (Women)	(6) Graduation (Women)
Post x Treatment	-14.233***	-15.764***	-9.344***	-4.208***	-2.409**	-4.021***
	(1.639)	(3.087)	(1.893)	(0.674)	(1.220)	(0.901)
Post	3.192***	8.265***	3.242**	2.492***	8.473***	2.080***
	(1.058)	(2.251)	(1.523)	(0.507)	(1.121)	(0.798)
Treatment	3.783***	5.664	3.866***	3.645***	12.924***	2.630***
	(1.449)	(5.199)	(1.457)	(0.670)	(2.575)	(0.714)
Control	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.12	0.13	0.12	0.13	0.14	0.12
Observations	6,018	6,018	6,018	6,018	6,018	6,018
Pre-COVID19 Mean Dep.	95.795	418.103	42.268	41.249	177.800	18.192
Effect as % of Pre-COVID19 Mean	14.85%	3.77%	22.1%	10.2%	1.35%	22.1%

Source: ANUIES.
Standard errors in parentheses. * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$)

Table A.5: Difference-in-difference results by gender: health

	(1) New entry (Men)	(2) Enrollment (Men)	(3) Graduation (Men)	(4) New entry (Women)	(5) Enrollment (Women)	(6) Graduation (Women)
Post x Treatment	-6.349***	-5.265*	-5.362***	-12.516***	-10.121	-11.575***
	(1.328)	(2.756)	(1.657)	(3.522)	(6.390)	(3.133)
Post	0.589	1.176	3.323***	4.318	15.258**	7.194***
	(1.251)	(2.364)	(1.191)	(3.352)	(6.062)	(2.446)
Treatment	-0.853	-8.497**	2.541**	-0.099	7.507	6.664***
	(1.313)	(3.863)	(1.290)	(2.722)	(7.998)	(2.516)
Control	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.09	0.14	0.10	0.09	0.15	0.13
Observations	3,330	3,330	3,330	3,330	3,330	3,330
Pre-COVID19 Mean Dep.	47.013	200.949	22.012	107.240	421.882	47.614
Effect as % of Pre-COVID19 Mean	13.5%	2.62%	24.35%	11.67%	2.39%	24.31%

Source: ANUIES.
Standard errors in parentheses. * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$)

Table A.6: Difference-in-difference results by gender: information technology

	(1) New entry (Men)	(2) Enrollment (Men)	(3) Graduation (Men)	(4) New entry (Women)	(5) Enrollment (Women)	(6) Graduation (Women)
Post x Treatment	-4.327***	0.109	-2.879***	-0.955**	1.732***	-0.876**
	(1.343)	(2.155)	(1.046)	(0.473)	(0.618)	(0.364)
Post	2.998	2.809	0.017	0.666	-0.430	-0.167
	(1.859)	(1.808)	(0.596)	(0.586)	(0.727)	(0.208)
Treatment	0.985	0.079	-0.408	0.525	-0.720	-0.653***
	(0.710)	(2.448)	(0.637)	(0.354)	(0.803)	(0.238)
Control	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.08	0.11	0.12	0.08	0.13	0.14
Observations	5,488	5,488	5,488	5,488	5,488	5,488
Pre-COVID19 Mean Dep.	33.658	132.518	13.273	10.256	40.734	5.411
Effect as % of Pre-COVID19 Mean	12.85%	0.008%	21.69%	9.31%	4.25%	16.18%

Source: ANUIES.
Standard errors in parentheses. * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$)

Table A.7: Difference-in-difference results by gender: business

	(1) New entry (Men)	(2) Enrollment (Men)	(3) Graduation (Men)	(4) New entry (Women)	(5) Enrollment (Women)	(6) Graduation (Women)
Post x Treatment	-8.051***	-6.715**	-2.511***	-8.096***	-4.767	-4.330***
	(1.485)	(3.212)	(0.716)	(2.256)	(3.433)	(1.029)
Post	2.697**	4.181**	0.232	3.848*	7.286**	0.783
	(1.290)	(2.080)	(0.573)	(2.070)	(2.868)	(0.813)
Treatment	0.516	-0.523	-0.351	1.081	2.514	0.012
	(0.810)	(2.688)	(0.493)	(0.896)	(3.193)	(0.709)
Control	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.05	0.08	0.09	0.06	0.09	0.12
Observations	11,044	11,044	11,044	11,044	11,044	11,044
Pre-COVID19 Mean Dep.	40.504	148.592	14.380	49.428	189.610	21.814
Effect as % of Pre-COVID19 Mean	19.87%	4.51%	17.46%	16.37%	2.51%	19.85%

Source: ANUIES.
Standard errors in parentheses. * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$)

Table A.8: Difference-in-difference results by gender: agronomy and veterinary

	(1) New entry (Men)	(2) Enrollment (Men)	(3) Graduation (Men)	(4) New entry (Women)	(5) Enrollment (Women)	(6) Graduation (Women)
Post x Treatment	-7.393***	-13.658***	-5.938***	-1.378	-1.709	-3.404*
	(2.466)	(3.259)	(2.100)	(1.531)	(2.102)	(1.980)
Post	0.399	4.179	1.667	0.850	9.619***	1.260
	(1.817)	(2.760)	(1.212)	(1.105)	(2.121)	(1.104)
Treatment	0.199	2.387	0.572	2.458*	17.025***	1.626
	(1.935)	(5.105)	(1.189)	(1.311)	(4.707)	(1.156)
Control	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.04	0.06	0.05	0.09	0.13	0.08
Observations	1,144	1,144	1,144	1,144	1,144	1,144
Pre-COVID19 Mean Dep.	56.870	226.033	21.750	37.130	147.271	12.388
Effect as % of Pre-COVID19 Mean	12.99%	6.04%	27.29%	3.71%	1.16%	27.47%

Source: ANUIES.
Standard errors in parentheses. * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$)

Table A.9: Difference-in-difference results by gender: arts and humanities

	(1) New entry (Men)	(2) Enrollment (Men)	(3) Graduation (Men)	(4) New entry (Women)	(5) Enrollment (Women)	(6) Graduation (Women)
Post x Treatment	-3.253***	-2.020**	-0.782**	-2.816***	0.203	-0.929*
	(0.726)	(0.966)	(0.386)	(0.811)	(0.928)	(0.546)
Post	0.916**	1.611**	0.234	1.490***	3.094***	0.138
	(0.397)	(0.723)	(0.371)	(0.395)	(0.574)	(0.556)
Treatment	1.263***	-0.626	-0.196	1.866***	1.291	-0.490
	(0.476)	(1.466)	(0.373)	(0.616)	(1.941)	(0.541)
Control	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.23	0.27	0.20	0.26	0.28	0.19
Observations	4,044	4,044	4,044	4,044	4,044	4,044
Pre-COVID19 Mean Dep.	20.152	72.529	5.791	25.256	93.045	8.864
Effect as % of Pre-COVID19 Mean	16.14%	2.78%	13.49%	11.15%	0.2%	10.47%

Source: ANUIES.
Standard errors in parentheses. * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$)

Table A.10: Difference-in-difference results by gender: services

	(1) New entry (Men)	(2) Enrollment (Men)	(3) Graduation (Men)	(4) New entry (Women)	(5) Enrollment (Women)	(6) Graduation (Women)
Post x Treatment	-6.292***	-3.662**	-1.546***	-4.099***	-1.780	-1.881***
	(1.897)	(1.557)	(0.449)	(0.832)	(1.661)	(0.541)
Post	2.048	0.198	0.638**	1.443*	1.014	0.410
	(1.830)	(1.757)	(0.313)	(0.762)	(1.355)	(0.377)
Treatment	1.392	-2.396	-0.626	1.244	-0.491	-0.752
	(0.975)	(2.248)	(0.399)	(0.880)	(2.076)	(0.478)
Control	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.05	0.10	0.10	0.09	0.16	0.10
Observations	3,038	3,038	3,038	3,038	3,038	3,038
Pre-COVID19 Mean Dep.	21.667	74.993	7.052	20.661	72.750	8.364
Effect as % of Pre-COVID19 Mean	29.03%	4.88%	21.92%	19.83%	2.44%	22.49%

Source: ANUIES.
Standard errors in parentheses. * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$)

Table A.11: Heterogeneous treatment effects (DDD): Sciences

	(1) New entry	(2) Enrollment	(3) Graduation
Panel A: Synchronous vs asynchronous			
Post=1 × Treatment=1 × Synchronous=1	46.411	-49.914*	-14.506
	(71.254)	(27.218)	(8.980)
Post=1 × Treatment=1	-51.159	53.659*	-2.833
	(71.321)	(27.917)	(3.226)
Pre-COVID19 Mean Dep. Synchronous=1	110.98	455.37	46.21
Pre-COVID19 Mean Dep. Synchronous=0	132.52	349.67	6.54
Relative effect as % of Pre-COVID19 Mean, Synchronous=1	41.81%	10.96%	31.38%
Panel B: Public vs private			
Post=1 × Treatment=1 × Public=1	0.240	2.770	-19.389*
	(6.255)	(10.354)	(10.574)
Post=1 × Treatment=1	-6.740**	5.800	-1.348
	(2.765)	(8.269)	(1.856)
Pre-COVID19 Mean Dep. Public	132.07	532.90	51.53
Pre-COVID19 Mean Dep. Private	42.01	152.54	16.82
Relative effect as % of Pre-COVID19 Mean, Public = 1	0.01%	0.05%	37.62%
Panel C: Top 20 vs Non-top 20			
Post=1 × Treatment=1 × Top 20=1	6.456	-15.398	-44.127
	(13.092)	(20.095)	(32.623)
Post=1 × Treatment=1	-8.201	11.451**	-6.015**
	(5.417)	(4.899)	(2.898)
Pre-COVID19 Mean Dep. Top20	221.53	1004.69	92.08
Pre-COVID19 Mean Dep. Non-Top 20	78.60	278.18	29.05
Relative effect as % of Pre-COVID19 Mean, Top 20=1	2.91%	1.53%	47.92%
Observations	1,058	1,058	1,058

Note: $^{***}p < 0.01$,** $p < 0.05$,* $p < 0.1$. Standard errors, clustered at the municipality level, are in parentheses. All regressions include controls and the R^2 vary between 0.06 to 0.14.

Table A.12: Heterogeneous treatment effects (DDD): Social Sciences

	(1) New entry	(2) Enrollment	(3) Graduation
Panel A: Synchronous vs asynchronous			
Post=1 × Treatment=1 × Synchronous=1	3.830	-2.569	-6.240**
	(4.944)	(10.314)	(2.812)
Post=1 × Treatment=1	-17.967***	-9.570	-4.772**
	(4.637)	(10.795)	(2.227)
Pre-COVID19 Mean Dep. Synchronous=1	92.83	370.17	45.37
Pre-COVID19 Mean Dep. Synchronous=0	69.27	219.87	18.43
Relative effect as % of Pre-COVID19 Mean, Synchronous=1	4.12%	0.06%	13.75%
Panel B: Public vs private			
Post=1 × Treatment=1 × Public=1	-0.601	16.981	-42.427***
	(8.240)	(13.408)	(11.319)
Post=1 × Treatment=1	-15.142***	-12.904**	-2.834***
	(1.761)	(5.551)	(0.916)
Pre-COVID19 Mean Dep. Public	275.14	1178.82	120.37
Pre-COVID19 Mean Dep. Private	54.20	180.59	22.6
Relative effect as % of Pre-COVID19 Mean, Public = 1	0.02%	1.44%	35.24%
Panel C: Top 20 vs Non-top 20			
Post=1 × Treatment=1 × Top 20=1	6.456	-15.398	-44.127
	(13.092)	(20.095)	(32.623)
Post=1 × Treatment=1	-8.201	11.451**	-6.015**
	(5.417)	(4.899)	(2.898)
Pre-COVID19 Mean Dep. Top20	221.53	1004.69	92.08
Pre-COVID19 Mean Dep. Non-Top 20	68.64	237.22	28.07
Relative effect as % of Pre-COVID19 Mean, Top 20=1	3.8%	0.06%	26.1%
Observations	9,940	9,940	9,940

Note: ***$p < 0.01$,** $p < 0.05$,* $p < 0.1$. Standard errors, clustered at the municipality level, are in parentheses. All regressions include controls and the R^2 vary between 0.06 to 0.14.

Table A.13: Heterogeneous treatment effects (DDD): Education

	(1) New entry	(2) Enrollment	(3) Graduation
Panel A: Synchronous vs asynchronous			
Post=1 × Treatment=1 × Synchronous=1	9.023	-0.195	4.261
	(5.674)	(7.457)	(3.362)
Post=1 × Treatment=1	-17.564***	0.995	-5.708*
	(4.891)	(7.004)	(3.311)
Pre-COVID19 Mean Dep. In-person	46.17	142.73	21.74
Pre-COVID19 Mean Dep. Synchronous=0	48.79	143.35	21.89
Relative effect as % of Pre-COVID19 Mean, Synchronous=1	19.54%	0.01%	19.6%
Panel B: Public vs private			
Post=1 × Treatment=1 × Public=1	-4.348	30.264***	-16.049***
	(6.006)	(9.627)	(6.176)
Post=1 × Treatment=1	-10.936***	-5.353*	0.363
	(2.045)	(3.091)	(0.790)
Pre-COVID19 Mean Dep. Public	100.14	340.01	51.79
Pre-COVID19 Mean Dep. Private	31.87	86.16	13.15
Relative effect as % of Pre-COVID19 Mean, Public = 1	4.34%	8.9%	30.98%
Panel C: Top 20 vs Non-top 20			
Post=1 × Treatment=1 × Top 20=1	25.281***	13.369	-6.338
	(8.934)	(10.022)	(8.332)
Post=1 × Treatment=1	-12.653***	0.604	-2.855*
	(2.117)	(3.301)	(1.506)
Pre-COVID19 Mean Dep. Top20	108.96	467.11	54.39
Pre-COVID19 Mean Dep. Non-Top 20	45.22	132.83	20.77
Relative effect as % of Pre-COVID19 Mean, Top 20=1	23.2%	2.86%	11.65%
Observations	5,566	5,566	5,566

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors, clustered at the municipality level, are in parentheses. All regressions include controls and the R^2 vary between 0.06 to 0.14.

Table A.14: Heterogeneous treatment effects (DDD): Engineering

	(1) New entry	(2) Enrollment	(3) Graduation
Panel A: Synchronous vs asynchronous			
Post=1 × Treatment=1 × Synchronous=1	-1.322	-21.726*	-11.781***
	(6.125)	(11.135)	(3.343)
Post=1 × Treatment=1	-17.685***	-0.769	-3.882**
	(5.412)	(10.321)	(1.639)
Pre-COVID19 Mean Dep. Synchronous=1	152.92	683.18	70.90
Pre-COVID19 Mean Dep. Synchronous=0	65.68	203.60	13.54
Relative effect as % of Pre-COVID19 Mean, Synchronous=1	0.08%	3.1%	16.61%
Panel B: Public vs private			
Post=1 × Treatment=1 × Public=1	2.772	5.471	-28.072***
	(4.845)	(7.982)	(5.363)
Post=1 × Treatment=1	-19.697***	-20.231***	-0.641
	(2.918)	(5.647)	(1.574)
Pre-COVID19 Mean Dep. Public	227.19	1049.78	107.37
Pre-COVID19 Mean Dep. Private	60.34	209.73	20.54
Relative effect as % of Pre-COVID19 Mean, Public = 1	1.22%	0.05%	26.14%
Panel C: Top 20 vs Non-top 20			
Post=1 × Treatment=1 × Top 20=1	19.950**	53.606**	-24.429
	(9.126)	(23.319)	(22.674)
Post=1 × Treatment=1	-20.021***	-22.110***	-11.250***
	(2.305)	(3.758)	(1.942)
Pre-COVID19 Mean Dep. Top 20	346.86	1789.29	173.79
Pre-COVID19 Mean Dep. Non-Top 20	117.80	486.47	50.06
Relative effect as % of Pre-COVID19 Mean, Top 20=1	5.75%	2.99%	14.05%
Observations	6,018	6,018	6,018

Note: $^{***}p < 0.01$,** $p < 0.05$,* $p < 0.1$. Standard errors, clustered at the municipality level, are in parentheses. All regressions include controls and the R^2 vary between 0.06 to 0.14.

Table A.15: Heterogeneous treatment effects (DDD): Health

	(1) New entry	(2) Enrollment	(3) Graduation
Panel A: Synchronous vs asynchronous			
Post=1 × Treatment=1 × Synchronous=1	-6.925	-9.304	3.981
	(24.810)	(24.492)	(12.177)
Post=1 × Treatment=1	-13.052	-7.501	-20.383*
	(24.426)	(22.215)	(11.697)
Pre-COVID19 Mean Dep. Synchronous=1	163.07	682.22	75.74
Pre-COVID19 Mean Dep. Synchronous=0	100.34	259.71	32.21
Relative effect as % of Pre-COVID19 Mean, Synchronous=1	4.24%	1.36%	5.25%
Panel B: Public vs private			
Post=1 × Treatment=1 × Public=1	5.846	16.544	-32.968**
	(13.117)	(16.973)	(13.217)
Post=1 × Treatment=1	-20.424***	-19.435*	-7.638**
	(3.710)	(11.026)	(3.177)
Pre-COVID19 Mean Dep. Public	281.93	1360.04	161.83
Pre-COVID19 Mean Dep. Private	103.60	330.40	33.05
Relative effect as % of Pre-COVID19 Mean, Public = 1	2.07%	1.21%	20.37%
Panel C: Top 20 vs Non-top 20			
Post=1 × Treatment=1 × Top 20=1	28.587***	53.670**	-38.919
	(8.627)	(21.610)	(27.552)
Post=1 × Treatment=1	-21.727***	-20.698**	-12.734***
	(5.081)	(9.726)	(3.858)
Pre-COVID19 Mean Dep. Top 20	316.09	1710.26	210.01
Pre-COVID19 Mean Dep. Non-Top 20	134.63	491.03	52.61
Relative effect as % of Pre-COVID19 Mean, Top 20=1	9.04%	3.13%	18.53%
Observations	3,330	3,330	3,330

Note: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. Standard errors, clustered at the municipality level, are in parentheses. All regressions include controls and the R^2 vary between 0.06 to 0.14.

Table A.16: Heterogeneous treatment effects (DDD): Information Technology

	(1) New entry	(2) Enrollment	(3) Graduation
Panel A: Synchronous vs asynchronous			
Post=1 × Treatment=1 × Synchronous=1	12.953	-6.930	-3.707***
	(8.893)	(10.891)	(1.357)
Post=1 × Treatment=1	-15.689*	6.679	-0.964
	(8.686)	(10.424)	(0.900)
Pre-COVID19 Mean Dep. Synchronous=1	45.97	191.44	22.35
Pre-COVID19 Mean Dep. Synchronous=0	36.46	107.38	5.41
Relative effect as % of Pre-COVID19 Mean, Synchronous=1	28.17%	3.61%	16.58%
Panel B: Public vs private			
Post=1 × Treatment=1 × Public=1	-2.232	2.902	-9.237***
	(3.950)	(7.000)	(2.801)
Post=1 × Treatment=1	-4.256***	0.547	0.440
	(1.510)	(4.598)	(0.406)
Pre-COVID19 Mean Dep. Public	75.42	313.35	33.96
Pre-COVID19 Mean Dep. Private	17.54	55.99	5.89
Relative effect as % of Pre-COVID19 Mean, Public = 1	2.95%	0.09%	27.19%
Panel C: Top 20 vs Non-top 20			
Post=1 × Treatment=1 × Top 20=1	6.889	17.052	-25.368
	(8.482)	(21.172)	(18.329)
Post=1 × Treatment=1	-5.724***	0.726	-2.127***
	(1.792)	(3.033)	(0.607)
Pre-COVID19 Mean Dep. Top20	137.65	667.98	62.65
Pre-COVID19 Mean Dep. Non-Top 20	37.54	139.65	15.69
Relative effect as % of Pre-COVID19 Mean, Top 20=1	5.00%	2.55%	40.48%
Observations	5,488	5,488	5,488

Note: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. Standard errors, clustered at the municipality level, are in parentheses. All regressions include controls and the R^2 vary between 0.06 to 0.14.

Table A.17: Heterogeneous treatment effects (DDD): Business

	(1) New entry	(2) Enrollment	(3) Graduation
Panel A: Synchronous vs asynchronous			
Post=1 × Treatment=1 × Synchronous=1	14.673	-11.404	-6.360***
	(9.933)	(11.573)	(2.105)
Post=1 × Treatment=1	-26.716***	-4.627	-2.729*
	(10.251)	(13.380)	(1.516)
Pre-COVID19 Mean Dep. Synchronous=1	94.29	383.62	45.40
Pre-COVID19 Mean Dep. Synchronous=0	80.44	239.38	16.16
Relative effect as % of Pre-COVID19 Mean, Synchronous=1	15.56%	2.97%	14.01%
Panel B: Public vs private			
Post=1 × Treatment=1 × Public=1	6.919	11.172	-19.975***
	(11.842)	(11.936)	(5.216)
Post=1 × Treatment=1	-17.951***	-14.158*	-1.217
	(3.018)	(8.585)	(0.784)
Pre-COVID19 Mean Dep. Public	165.17	699.68	75.50
Pre-COVID19 Mean Dep. Private	59.36	191.33	20.22
Relative effect as % of Pre-COVID19 Mean, Public = 1	4.18%	1.59%	26.45%
Panel C: Top 20 vs Non-top 20			
Post=1 × Treatment=1 × Top 20=1	49.334***	46.801*	-11.273
	(16.146)	(27.609)	(22.661)
Post=1 × Treatment=1	-18.824***	-13.943**	-6.285***
	(3.771)	(6.692)	(1.120)
Pre-COVID19 Mean Dep. Top20	278.41	1,311.37	144.90
Pre-COVID19 Mean Dep. Non-Top 20	78.84	280.95	29.79
Relative effect as % of Pre-COVID19 Mean, Top 20=1	17.71%	3.56%	7.78%
Observations	11,044	11,044	11,044

Note: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. Standard errors, clustered at the municipality level, are in parentheses. All regressions include controls and the R^2 vary between 0.06 to 0.11.

Table A.18: Heterogeneous treatment effects (DDD): Agronomy and Veterinary

	(1) New entry	(2) Enrollment	(3) Graduation
Panel A: Synchronous vs asynchronous			
Post=1 × Treatment=1 × Synchronous=1	-31.501	-25.545	-4.255
	(23.686)	(29.303)	(5.624)
Post=1 × Treatment=1	20.319	8.872	-5.653
	(23.436)	(28.904)	(3.822)
Pre-COVID19 Mean Dep. Synchronous=1	98.90	395.48	36.70
Pre-COVID19 Mean Dep. Synchronous=0	39.74	127.81	5.82
Relative effect as % of Pre-COVID19 Mean, Synchronous=1	31.85%	6.45%	11.59%
Panel B: Public vs private			
Post=1 × Treatment=1 × Public=1	9.010	3.228	-15.786**
	(7.445)	(13.849)	(7.539)
Post=1 × Treatment=1	-16.264**	-18.096	3.791
	(6.325)	(12.771)	(4.913)
Pre-COVID19 Mean Dep. Public	102.04	414.15	38.76
Pre-COVID19 Mean Dep. Private	52.83	164.02	10.44
Relative effect as % of Pre-COVID19 Mean, Public = 1	8.82%	0.7%	40.72%
Panel C: Top 20 vs Non-top 20			
Post=1 × Treatment=1 × Top 20=1	4.209	12.762	-23.065
	(7.603)	(15.737)	(21.818)
Post=1 × Treatment=1	-9.255**	-16.713***	-6.399**
	(4.109)	(5.060)	(3.137)
Pre-COVID19 Mean Dep. Top20	150.62	732.58	65.90
Pre-COVID19 Mean Dep. Non-Top 20	85.25	317.84	29.23
Relative effect as % of Pre-COVID19 Mean, Top 20=1	2.79%	1.74%	34.99%
Observations	1,144	1,144	1,144

Note: $^{***}p < 0.01$,** $p < 0.05$,* $p < 0.1$. Standard errors, clustered at the municipality level, are in parentheses. All regressions include controls and the R^2 vary between 0.05 to 0.09.

Table A.19: Heterogeneous treatment effects (DDD): Arts and Humanities

	(1) New entry	(2) Enrollment	(3) Graduation
Panel A: Synchronous vs asynchronous			
Post=1 × Treatment=1 × Synchronous=1	-0.573	0.596	-0.705
	(3.627)	(5.483)	(1.419)
Post=1 × Treatment=1	-5.714	-2.346	-1.140
	(3.678)	(4.950)	(1.223)
Pre-COVID19 Mean Dep. Synchronous=1	48.79	183.52	16.66
Pre-COVID19 Mean Dep. Synchronous=0	30.32	85.53	5.71
Relative effect as % of Pre-COVID19 Mean, Synchronous=1	1.17%	0.3%	4.23%
Panel B: Public vs private			
Post=1 × Treatment=1 × Public=1	-5.186	3.782	-10.295**
	(5.826)	(7.977)	(4.045)
Post=1 × Treatment=1	-5.158***	-2.526	0.099
	(1.409)	(1.727)	(0.540)
Pre-COVID19 Mean Dep. Public	130.92	541.33	40.85
Pre-COVID19 Mean Dep. Private	27.13	85.27	9.05
Relative effect as % of Pre-COVID19 Mean, Public = 1	3.96%	0.69%	25.19%
Panel C: Top 20 vs Non-top 20			
Post=1 × Treatment=1 × Top 20=1	-0.472	4.282	-9.602
	(6.924)	(15.620)	(10.045)
Post=1 × Treatment=1	-6.020***	-2.043	-1.084**
	(1.626)	(1.727)	(0.500)
Pre-COVID19 Mean Dep. Top20	195.57	898.52	70.68
Pre-COVID19 Mean Dep. Non-Top 20	34.93	114.46	10.74
Relative effect as % of Pre-COVID19 Mean, Top 20=1	0.24%	0.47%	13.58%
Observations	4,044	4,044	4,044

Note: $^{***}p < 0.01$,$^{**}p < 0.05$,$^{*}p < 0.1$. Standard errors, clustered at the municipality level, are in parentheses. All regressions include controls and the R^2 vary between 0.20 to 0.28.

Table A.20: Heterogeneous treatment effects (DDD): Services

	(1) New entry	(2) Enrollment	(3) Graduation
Panel A: Synchronous vs asynchronous			
Post=1 × Treatment=1 × Synchronous=1	21.748	9.434	-4.703**
	(19.540)	(11.617)	(2.039)
Post=1 × Treatment=1	-29.138	-13.767	0.484
	(19.195)	(11.757)	(1.610)
Pre-COVID19 Mean Dep. Synchronous=1	40.85	149.03	17.11
Pre-COVID19 Mean Dep. Synchronous=0	50.82	140.37	5.73
Relative effect as % of Pre-COVID19 Mean, Synchronous=1	53.24%	6.33%	27.49%
Panel B: Public vs private			
Post=1 × Treatment=1 × Public=1	-6.845	6.788	-8.540***
	(10.600)	(9.470)	(2.949)
Post=1 × Treatment=1	-8.537***	-7.116***	-1.192*
	(1.255)	(1.970)	(0.644)
Pre-COVID19 Mean Dep. Public	80.51	331.98	32.29
Pre-COVID19 Mean Dep. Private	28.67	81.86	9.38
Relative effect as % of Pre-COVID19 Mean, Public = 1	8.50%	2.04%	26.44%
Panel C: Top 20 vs Non-top 20			
Post=1 × Treatment=1 × Top20=1	12.322***	37.951*	-2.580
	(4.008)	(21.310)	(3.957)
Post=1 × Treatment=1	-11.112***	-7.624***	-3.298***
	(2.702)	(2.641)	(0.940)
Pre-COVID19 Mean Dep. Top20	98.68	454.65	34.86
Pre-COVID19 Mean Dep. Non-Top 20	38.68	127.88	14.15
Relative effect as % of Pre-COVID19 Mean, Top 20=1	12.48%	8.34%	7.40%
Observations	3,038	3,038	3,038

Note: $^{***}p < 0.01$,** $p < 0.05$,* $p < 0.1$. Standard errors, clustered at the municipality level, are in parentheses. All regressions include controls and the R^2 vary between 0.07 to 0.14.

Table A.21: Difference-in-difference results: placebo

	(1) New entry	(2) Enrollment	(3) Graduation
Sciences			
Post x Treatment	1.768	22.658	-5.218
	(2.085)	(18.324)	(6.350)
R^2	0.09	0.13	0.09
Observations	1,036	1,036	1,036
Social Sciences			
Post x Treatment	-1.431	-3.723	-0.884
	(1.690)	(4.631)	(1.287)
R^2	0.11	0.14	0.12
Observations	9,484	9,484	9,484
Education			
Post x Treatment	0.050	9.637***	-1.826
	(1.712)	(3.231)	(1.552)
R^2	0.12	0.17	0.11
Observations	5,198	5,198	5,198
Engineering			
Post x Treatment	4.040*	-3.394	-0.330
	(2.317)	(5.093)	(1.750)
R^2	0.13	0.14	0.13
Observations	5,676	5,676	5,676
Health			
Post x Treatment	-3.130	-5.145	-3.492
	(3.511)	(5.851)	(3.404)
R^2	0.08	0.14	0.12
Observations	3,130	3,130	3,130
Information Technology			
Post x Treatment	-0.594	8.854	-0.315
	(0.861)	(9.486)	(0.784)
R^2	0.07	0.10	0.14
Observations	5,328	5,328	5,328
Business			
Post x Treatment	0.013	3.451	-0.426
	(2.242)	(9.668)	(1.065)
R^2	0.05	0.09	0.11
Observations	10,524	10,524	10,524
Agronomy & Veterinary			
Post x Treatment	-1.842	-7.764**	-2.781
	(2.146)	(3.592)	(2.124)
R^2	0.05	0.09	0.06
Observations	1,088	1,088	1,088

Arts & Humanities			
Post x Treatment	2.526**	6.519**	-0.016
	(1.123)	(2.748)	(0.607)
R^2	0.25	0.28	0.21
Observations	3,856	3,856	3,856
Services			
Post x Treatment	4.428**	14.261	-1.316
	(2.029)	(12.566)	(0.984)
R^2	0.05	0.10	0.11
Observations	2,874	2,874	2,874

Source: ANUIES.
Standard errors in parentheses. * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$)

Table A.23: Difference-in-difference results: robustness analysis - q-values

	(1) New entry	(2) Enrollment	(3) Graduation
Sciences			
Post x Treatment	-6.730	7.626	-16.489**
	(0.163)	(0.235)	(0.046)
	[0.139]	[0.162]	[0.074]
R^2	0.10	0.13	0.09
Observations	1,058	1,058	1,058
Social Sciences			
Post x Treatment	-15.259***	-10.763**	-8.633***
	(4.17e-15)	(0.035)	(1.66e-09)
	[0.001]	[0.029]	[0.001]
R^2	0.12	0.14	0.12
Observations	9,940	9,940	9,940
Education			
Post x Treatment	-11.906***	0.981	-3.025**
	(1.54e-08)	(0.758)	(0.045)
	[0.001]	[0.22]	[0.04]
R^2	0.13	0.17	0.10
Observations	5,566	5,566	5,566
Engineering			
Post x Treatment	-18.442***	-18.173***	-13.365***
	(2.13e-16)	(1.01e-5)	(3.68e-7)
	[0.001]	[0.001]	[0.001]
R^2	0.13	0.14	0.12
Observations	6,018	6,018	6,018
Health			
Post x Treatment	-18.865***	-15.386*	-16.937***
	(4.98e-5)	(0.084)	(0.0003)
	[0.001]	[0.054]	[0.002]
R^2	0.09	0.15	0.13
Observations	3,330	3,330	3,330
Information Technology			
Post x Treatment	-5.282***	1.841	-3.755***
	(0.002)	(0.490)	(0.006)
	[0.007]	[0.279]	[0.012]
R^2	0.08	0.11	0.12
Observations	5,488	5,488	5,488
Business			
Post x Treatment	-16.147***	-11.482*	-6.841***
	(1.43e-05)	(0.080)	(7.11e-05)
	[0.001]	[0.045]	[0.001]
R^2	0.06	0.09	0.11

Observations	11,044	11,044	11,044
Agronomy & Veterinary			
Post x Treatment	-8.771**	-15.367***	-9.341**
	(0.016)	(0.001)	(0.014)
	[0.022]	[0.004]	[0.022]
R^2	0.05	0.09	0.06
Observations	1,144	1,144	1,144
Arts & Humanities			
Post x Treatment	-6.070***	-1.817	-1.710**
	(4.17e-05)	(0.292)	(0.043)
	[0.001]	[0.095]	[0.024]
R^2	0.25	0.28	0.20
Observations	4,044	4,044	4,044
Services			
Post x Treatment	-10.391***	-5.442*	-3.428***
	(5.82e-05)	(0.053)	(0.0002)
	[0.001]	[0.075]	[0.001]
R^2	0.07	0.14	0.12
Observations	3,038	3,038	3,038

Source: ANUIES.
p-values in parenthesis and q-values in brackets.

Table A.22: Difference-in-difference results by gender (placebo)

	(1) New entry (Men)	(2) Enrollment (Men)	(3) Graduation (Men)	(4) New entry (Women)	(5) Enrollment (Women)	(6) Graduation (Women)
Sciences						
Post x Treatment	1.150	15.071	-0.952	0.618	7.587	-4.267
	(1.199)	(11.687)	(2.181)	(1.337)	(6.736)	(4.295)
R^2	0.09	0.12	0.10	0.09	0.13	0.08
Observations	1,036	1,036	1,036	1,036	1,036	1,036
Social Sciences						
Post x Treatment	-0.541	-1.480	-0.454	-0.889	-2.242	-0.430
	(0.696)	(2.103)	(0.485)	(1.082)	(2.670)	(0.859)
R^2	0.10	0.12	0.11	0.11	0.14	0.13
Observations	9,484	9,484	9,484	9,484	9,484	9,484
Education						
Post x Treatment	-0.291	2.923***	-0.545	0.341	6.714***	-1.281
	(0.598)	(1.123)	(0.525)	(1.268)	(2.314)	(1.121)
R^2	0.08	0.13	0.10	0.11	0.16	0.10
Observations	5,198	5,198	5,198	5,198	5,198	5,198
Engineering						
Post x Treatment	2.712	-2.629	-0.268	1.328*	-0.765	-0.061
	(1.717)	(3.831)	(1.203)	(0.735)	(1.438)	(0.733)
R^2	0.12	0.13	0.13	0.14	0.14	0.13
Observations	5,676	5,676	5,676	5,676	5,676	5,676
Health						
Post x Treatment	0.371	-2.818	-1.262	-3.502	-2.327	-2.231
	(1.343)	(2.067)	(1.270)	(2.395)	(4.053)	(2.334)
R^2	0.08	0.13	0.10	0.08	0.15	0.13
Observations	3,130	3,130	3,130	3,130	3,130	3,130
Information Technology						
Post x Treatment	-0.826	6.065	-0.331	0.232	2.790	0.015
	(0.763)	(7.829)	(0.565)	(0.292)	(1.696)	(0.268)
R^2	0.07	0.10	0.12	0.08	0.13	0.15
Observations	5,328	5,328	5,328	5,328	5,328	5,328
Business						
Post x Treatment	-0.301	1.171	-0.296	0.314	2.281	-0.130
	(1.232)	(4.169)	(0.435)	(1.064)	(5.534)	(0.684)
R^2	0.05	0.08	0.09	0.05	0.10	0.12
Observations	10,524	10,524	10,524	10,524	10,524	10,524
Agronomy & Veterinary						
Post x Treatment	-0.787	-5.246**	-2.066	-1.054	-2.518	-0.715
	(1.551)	(2.106)	(1.547)	(1.094)	(1.972)	(0.783)
R^2	0.03	0.06	0.05	0.09	0.13	0.08
Observations	1,088	1,088	1,088	1,088	1,088	1,088
Arts & Humanities						
Post x Treatment	1.032*	2.588**	0.203	1.494**	3.931**	-0.218
	(0.548)	(1.180)	(0.252)	(0.701)	(1.685)	(0.412)
R^2	0.23	0.27	0.20	0.26	0.28	0.19
Observations	3,856	3,856	3,856	3,856	3,856	3,856
Services						
Post x Treatment	2.610**	11.230	-0.423	1.818**	3.031	-0.894
	(1.302)	(8.833)	(0.514)	(0.859)	(3.954)	(0.574)
R^2	0.04	0.07	0.10	0.06	0.13	0.10
Observations	2,874	2,874	2,874	2,874	2,874	2,874

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.24: Difference-in-difference results by gender: robustness analysis - q-values

	(1) New entry (Men)	(2) Enrollment (Men)	(3) Graduation (Men)	(4) New entry (Women)	(5) Enrollment (Women)	(6) Graduation (Women)
Sciences						
Post x Treatment	-3.980	2.135	-6.909**	-2.750	5.491	-9.580*
	(0.132)	(0.521)	(0.024)	(0.274)	(0.116)	(0.075)
	[0.14]	[0.313]	[0.042]	[0.195]	[0.126]	[0.094]
R^2	0.09	0.12	0.10	0.10	0.13	0.08
Observations	1,058	1,058	1,058	1,058	1,058	1,058
Social Sciences						
Post x Treatment	-6.971***	-6.080***	-2.884***	-8.288***	-4.683	-5.749***
	(3.93e-16)	(0.009)	(2.47e-5)	(4.08-e13)	(0.101)	(7.32e-7)
	[0.001]	[0.009]	[0.001]	[0.001]	[0.063]	[0.001]
R^2	0.11	0.13	0.11	0.12	0.15	0.12
Observations	9,940	9,940	9,940	9,940	9,940	9,940
Education						
Post x Treatment	-3.284***	-0.414	-0.709	-8.623***	1.395	-2.316**
	(6.82e-6)	(0.682)	(0.109)	(6.6e-9)	(0.558)	(0.044)
	[0.001]	[0.001]	[0.087]	[0.001]	[0.245]	[0.045]
R^2	0.09	0.13	0.09	0.12	0.17	0.09
Observations	5,566	5,566	5,566	5,566	5,566	5,566
Engineering						
Post x Treatment	-14.233***	-15.764***	-9.344***	-4.208***	-2.409**	-4.021***
	(5.8e-7)	(4.69e-7)	(1.1e-6)	(9.38e-10)	(0.048)	(9.94e-6)
	[0.001]	[0.001]	[0.001]	[0.001]	[0.012]	[0.001]
R^2	0.12	0.13	0.12	0.13	0.14	0.12
Observations	6,018	6,018	6,018	6,018	6,018	6,018
Health						
Post x Treatment	-6.349***	-5.265*	-5.362***	-12.516***	-10.121	-11.575***
	(2.8e-6)	(0.057)	(0.001)	(0.0004)	(0.114)	(0.0002)
	[0.001]	[0.041]	[0.004]	[0.002]	[0.068]	[0.001]
R^2	0.09	0.14	0.10	0.09	0.15	0.13
Observations	3,330	3,330	3,330	3,330	3,330	3,330
Information Technology						
Post x Treatment	-4.327***	0.109	-2.879***	-0.955**	1.732***	-0.876**
	(0.001)	(0.959)	(0.006)	(0.044)	(0.005)	(0.016)
	[0.005]	[0.434]	[0.011]	[0.047]	[0.011]	[0.022]
R^2	0.08	0.11	0.12	0.08	0.13	0.14
Observations	5,488	5,488	5,488	5,488	5,488	5,488
Business						
Post x Treatment	-8.051***	-6.715**	-2.511***	-8.096***	-4.767	-4.330***
	(8.60e-08)	(0.036)	(0.0004)	(0.0003)	(0.165)	(2.98e-05)
	[0.001]	[0.024]	[0.001]	[0.001]	[0.084]	[0.001]
R^2	0.05	0.08	0.09	0.06	0.09	0.12
Observations	11,044	11,044	11,044	11,044	11,044	11,044
Agronomy & Veterinary						
Post x Treatment	-7.393***	-13.658***	-5.938***	-1.378	-1.709	-3.404*
	(0.003)	(0.00003)	(0.005)	(0.368)	(0.416)	(0.086)
	[0.007]	[0.001]	[0.001]	[0.235]	[0.254]	[0.079]
R^2	0.04	0.06	0.05	0.09	0.13	0.08
Observations	1,144	1,144	1,144	1,144	1,144	1,144
Arts & Humanities						
Post x Treatment	-3.253***	-2.020**	-0.782**	-2.816***	0.203	-0.929*
	(1.13e-05)	(0.037)	(0.043)	(0.0006)	(0.826)	(0.090)
	[0.001]	[0.024]	[0.028]	[0.001]	[0.267]	[0.043]
R^2	0.23	0.27	0.20	0.26	0.28	0.19
Observations	4,044	4,044	4,044	4,044	4,044	4,044
Services						
Post x Treatment	-6.292***	-3.662**	-1.546***	-4.099***	-1.780	-1.881***
	(0.001)	(0.019)	(0.0006)	(1.50e-06)	(0.284)	(0.0005)
	[0.004]	[0.037]	[0.003]	[0.001]	[0.206]	[0.003]
R^2	0.05	0.10	0.10	0.09	0.16	0.10
Observations	3,038	3,038	3,038	3,038	3,038	3,038

p-values in parenthesis and q-values in brackets.

Table A.25: Descriptive Statistics: STEM vs Non-STEM

	STEM		Non-STEM	
	Mean	St.Dev.	Mean	St.Dev.
Pre-COVID 19				
Intake gap	26.52	127.08	-21.76	77.59
Enrollment gap	124.61	623.25	-83.15	293.08
Graduation gap	10.11	70.78	-13.77	48.22
N	7,254		12,492	
Post-COVID 19				
Intake gap	19.15	124.10	-23.14	78.78
Enrollment gap	100.80	634.76	-94.43	329.70
Graduation gap	6.49	64.81	-10.56	39.49
N	2,580		4,552	

Source: ANUIES.
Standard errors in parentheses. * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$).

Table A.26: Difference-in-difference results: STEM and Non-STEM Gender Gap Placebo Test

	(1) New entry	(2) Enrollment	(3) Graduation
STEM Gender Gap			
Post x Treatment	1.612	1.349	0.315
	(1.241)	(5.240)	(0.942)
Control	Yes	Yes	Yes
R^2	0.06	0.05	0.03
Observations	9,360	9,360	9,360
Non-STEM Gender Gap			
Post x Treatment	-0.420	-0.802	0.134
	(0.803)	(1.157)	(0.500)
Control	Yes	Yes	Yes
R^2	0.04	0.07	0.07
Observations	16,192	16,192	16,192

Source: ANUIES.
Standard errors in parentheses. * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$).