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Testing the Grades

A Study on the Impact of Online Education during COVID-19 on Student Grades

by

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Abstract

This study explores the relationship between online education and student grades at Lund University School of Economics and Management (LUSEM) during the COVID-19 pandemic. By investigating the learning environment's impact on student grades in this setting, we can take advantage of the recommendations of online education in higher education in Sweden, which resulted in an unprecedented sample size of student grades. We explore unique data on student grades from Ladok, covering data on the majority of LUSEMs departments and largest courses. The estimates portray ambiguous results of how online education has impacted student grades, where different groups and levels of studies have been affected differently. Several methodological approaches have been applied to the dataset to explore multiple nuances of the online learning environment's impact on student grades, including the non-parametric Wilcoxon rank-sum test, Ordinary Least Squares and Difference-in-Difference estimations. Moreover, we use Regression Discontinuity Design to visualize how the grades have changed during online education.

Key words: *Online education, student grades, COVID-19, Lund University School of Economics and Management (LUSEM)*

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1 Introduction

The COVID-19 pandemic came as a shock to the world and successively became a health threat to the public. As the spread of the COVID-19 virus continued, nations worldwide started to impose different restrictions to mitigate the escalation of the virus spread. A common measure was to implement lock-downs and school closures, resulting in an intensified usage of online learning tools for students worldwide (World Economic Forum 2020). Despite Sweden, in general, imposing relatively light policies to restrict the virus spread, the government imposed some stringent restriction measures, such as recommending universities to have their education online (Hale, Angrist, Goldszmidt, Kira, Petherick, Phillips, Webster, Cameron-Blake, Hallas, Majumdar & Tatlow 2021). The recommendation for universities to have their education online came in March 2020 and continued to be recommended throughout 2020 and a large part of 2021.

Previous literature, such as Karadag (2021), Halloran et al. (2021) and Kuhfeld et al. (2020) find ambiguous impacts of online education on student outcomes. Although some previous literature on online education and grading already exists, the magnitude of the COVID-19 pandemic and its impact on Swedish university closures results in unprecedented data on student outcomes. Therefore, the COVID-19 pandemic constitutes an external chock providing a unique opportunity to study the impact of online education on student outcomes. We take advantage of the pandemic and its subsequent restrictions to study online education's impact on student grades. Furthermore, in a regular setting where instructors and students can freely choose whether to enroll in online or on-campus education, the impact of the teaching mode is challenging to disentangle since there might be selection bias. Therefore, the situation with the national restrictions affecting all students and instructors at the same time makes it possible to ignore some of the selection bias that otherwise comes with online education.

Accordingly, this study investigates the grading outcomes at Lund Unversity School of Economics and Management (LUSEM) during the COVID-19 pandemic. We evaluate how the transition to online education has impacted student grades by analyzing a previously non-explored data set constituting student grade results at LUSEM, which is interesting for multiple reasons. Firstly, it is essential to understand the general dynamics of how online education has affected student outcomes. Secondly, it is also essential to understand the impact among several groups at LUSEM. Therefore, we analyze differential impacts among several groups: female and male students, undergraduate and master's students, math students, and several departments at LUSEM.

Although the COVID-19 constitutes a precarious situation, comprehending these dynamics is crucial to understanding how to act if a similar sudden shock occurs in the future. Also, the findings from this study could raise awareness of how online education can be integrated into higher education. Furthermore, we also argue that the results provided by this study could generate helpful information for other departments at Lund University and other universities in Sweden. For example, it is essential to dissect how instructors, students, and the organization have responded to the pandemic and its consequences.

To estimate the impact of online education on grades at LUSEM, we will explore a unique dataset consisting of individual-level data. This dataset spans from January 2017 to August 2021, allowing us to examine a sufficient period before and after the inclusion of online education. A combination of methods has been used to investigate the research questions: Wilcoxon rank-sum test, Ordinary Least Squares, Difference-in-Difference, and Regression Discontinuity Design. We will address two main research questions in this study, which are the following:

1. Has online education impacted the grade outcomes during the COVID-19 pandemic at LUSEM?
2. Has there been a differential impact across different groups?

This study finds that the average grades, in general, have decreased during online education at the Department of Economics compared to normal settings, but some groups have experienced increased grades. Our OLS estimations find a significant positive impact of online education on grades when covering the whole period. Similarly, we find a significant positive impact of online examinations when we narrow the period down to courses having examinations just after the 17th of March 2020. Additionally, the DiD estimation shows that NEKA12 has experienced lower average grades when shifting to online education than the control group NEKKPA.

Nevertheless, one limitation of this study is that students' grades during the COVID-19 pandemic can result from simultaneous factors affecting students' learning process. Thus, besides solely education mode, there might be other factors that have pushed the grades in a specific direction. Therefore, to account for other factors that have impacted grades during the COVID-19 pandemic, we will combine theoretical knowledge and empirical findings to discuss potential explanations that might have affected students grading outcomes, such as mental illness, cheating, and the role of the teacher. However, these possible explanations are challenging to test and difficult to identify. Therefore, even though we cannot isolate these explanations, we argue that highlighting those possible mechanisms is still relevant to understanding some of our results and provide a profound basis for further research.

The remainder of this paper is organized as follows: Section 2 will highlight the background by presenting the literature review and possible explanations. Section 3 will describe the institutional framework by providing some knowledge of the LUSEMs organization and the timeline with relevant dates. In Section 4, the data and variables included in our estimations will be reported. Furthermore, Section 5 will demonstrate the methodological framework for the study, while Section 6 will describe the results of the estimations. Section 7 will contextualize our findings by comparing our results with estimates from previous research and discussing potential explanations based on the theoretical framework. Lastly, Section 8 will conclude the results and present suggestions for further research.

2 Background

2.1 Literature Review

Several studies have examined the impact of the COVID-19 pandemic on grades in higher education, such as Karadag (2021) who explores the impact on grades in five universities in Turkey. In the study, the author covers data from 2 841 courses, and the study includes observations from approximately 150 000 students. Using an ANOVA approach, the study finds that the COVID-19 pandemic resulted in increased grades. Specifically, the results suggest that grades increased by approximately 9.2% during one year, which according to Karadag (2021) is the highest grade inflation ever reported in the literature.

Furthermore, the study by Karadag (2021) demonstrates that grades were differently affected by the COVID-19 crisis. For example, the study illustrates that the highest grade increased by 41% during the pandemic, while lower grades decreased between 31% and 55%. According to Karadag (2021), one explanation behind the changed grades during the sudden shift to online education was the difficulty for teachers to adapt to new technology and online education pedagogy. Also, Karadag (2021) stresses that student grades might have increased during the COVID-19 pandemic since instructors compensated students for the unfavorable circumstances.

Another interesting dimension of the study by Karadag (2021) is that there are differential impacts across more junior students compared to senior students. Specifically, the author argues that junior students are generally enrolled in courses with more students, making it more challenging to adapt to the online education environment. The findings of Karadag (2021) connect to our study since we, similar to them, are interested in heterogeneous impacts of changed grades during the COVID-19 pandemic in higher education.

Furthermore, another study on the area of online education and grades is proposed by Halloran, Jack, Okun & Oster (2021), who examine the impact of online education during the COVID-19 pandemic on student outcomes. They use students' test scores as the outcome variable to study the impact of on-campus education versus online education on student outcomes. To estimate this impact, they use a difference-in-difference (DiD) regression approach at the district-year level, making it possible to disentangle differential effects in different states in the United States. As a treatment, they use the share of the school year that the district provided full on-campus education. Moreover, the untreated group is the districts providing hybrid or virtual education. In line with Halloran et al. (2021), we will also apply a DiD-approach, adjusted to our circumstances.

By combining data on standardized test scores from the spring of 2021 from 12 states, Halloran et al. (2021) found that pass rates decreased relative to previous years in all states. However, the most dramatic decreases in pass rates occurred in states with low levels of on-campus teaching. They also investigated whether the impact on student test scores differed among academic subjects and found some heterogeneity in how different subjects were affected. For example, Halloran et al. (2021) found different impacts on math and English Language Arts (ELA) courses, where the average pass rate decreased by 14.2% in math and by 6.3% in ELA. When comparing the pass rates in states that offered full in-person teaching instead of hybrid or virtual teaching, the pass rates in math were 10.1% higher in states that offered in-person teaching. In the case of ELA pass rates, the pass rates were 3.2% higher in states offering in-person teaching.

The significant relationship between schooling mode and test scores found by Halloran et al. (2021) suggests that pass rates decreased compared to years before the COVID-19 pandemic. Also, the declines in pass rates were more prominent in states providing less on-campus education. Furthermore, another dimension that Halloran et al. (2021) adds to the relationship between educational mode and student test scores is whether the impact differed among students who are Black, Hispanic, and with lower socioeconomic status. Unfortunately, we cannot estimate such differential impacts across different ethnic or socioeconomic groups due to data limitations. Nevertheless, to add some nuances to the impact of online education, we will estimate the effect of online education among different groups, subjects, levels of education, and institutions.

Likewise, also Kuhfeld, Soland, Tarasawa, Johnson, Ruzek & Liu (2020) explore the impact of online education on student outcomes. By comparing students' grades during the fall of 2019 with the grades during the fall of 2020, they found that reading scores did not significantly change. However, they found that math grades were about 5 to 10% lower during spring 2020 compared to fall 2019. These results suggest that math grades might be more negatively affected by the COVID-19 pandemic compared to more qualitative subjects. Nevertheless, the study examined students in grades 3 to 8. Therefore, the grades are explored in a setting considerably younger than our study focusing on university students. However, the study by Kuhfeld et al. (2020) still provides valuable insights into how the COVID-19 pandemic has resulted in different effects across subjects.

Further studies that have examined the impact during the COVID-19 pandemic can be exemplified by Varmaz & Veith (2021) who studies the impact of online learning on student outcomes in German universities. They use the COVID-19 pandemic as an identification strategy in their difference-in-difference model and examine the impact of instruction mode on students' average exam results. By examining the period during the summer of 2020, the authors argue that they overcame the issue of selection bias since instructors were obliged to conduct the education online in the whole of Germany during this time. The findings in Varmaz & Veith (2021) mask interesting results on how the exam results changed before and after the COVID-19 pandemic, and they demonstrate that the transition from on-campus to online education resulted in better grades for the students.

Additionally, another study on student outcomes during the COVID-19 pandemic is performed by Breaux, Dunn, Langberg, Cusick, Dvorsky & Becker (2022) who examines whether students' GPAs have been deferentially affected for females and males and at-risk high school students. The classification of at-risk students includes students with pre-established learning difficulties such as attention-deficit-hyperactivity-disorder (ADHD) and students from disadvantaged families and racial minorities. Their results suggest that at-risk high school students were more negatively affected by the COVID-19 pandemic than non-risk high school students.

Due to limitations in data, we cannot explore a similar dimension as Breaux et al. (2022) in our study. However, regarding the differences between female and male students, Breaux et al. (2022) finds a significant adverse effect in male students' GPAs, while female students' GPAs were not significantly affected by the COVID-19 pandemic. These results reinforce that online education has deferentially impacted female and male students during the COVID-19 pandemic. Additionally, the result highlights that online education might have had a more significant adverse effect on more disadvantaged students, stressing heterogeneous impacts across different groups.

As mentioned in this chapter, some previous literature on online education during the COVID-19 pandemic exists. However, most studies are conducted on pupils of lower ages than university students. Thus, the link between online education and grades remains relatively unexplored for university students, and, to the author's knowledge, a similar study has not been made recently at Swedish universities. Thus, our study's main contribution is exploring the grades at the university level in Sweden.

Table 1: Summary of Previous Literature

Author(s)	**Level of education**	**Country**	**Method**	**Main results**
Varmaz & Veith (2021)	University	Germany	DiD	Increased grades. No size of coefficients mentioned.
Karadag (2021)	University	Turkey	ANOVA	Increased grades in general (9.2%). Higher grades increased more than lower grades.
Breaux et al. (2022)	Grade 11 to 12	United States	Survey on GPA's	No significant effect for female students. Male students grades decreased.
Halloran et al. (2021)	Grade 3 to 8	United States	DiD	Decreased grades. Higher decrease in Math (-14.2%) than ELA (-6.3%).
Kuhfeld et al. (2020)	Grade 3 to 8	United States	NWEA'S longitudal student achievement database	No significant effect for reading scores. Math scores decreased by 5%-10%.

2.2 Possible Explanations

In the case of online education during the COVID-19 pandemic, there ought to be multiple explanations for how it has impacted student grades. Although there is a possibility that there exists some link between educational quality and grade outcomes, studies such as Perry & Johnson (2004) and Vlachos (2010) imply that increased grades do not necessarily reflect more productive learning or better education. For example, they argue that higher grades could occur without increased productivity; thus, higher grades could equal grade inflation. Accordingly, we assume that increased grades do not necessarily reflect better education or higher productivity and define a student grade as an imperfect signal of educational quality.

Since we assume that the change in grades is not a direct response to a change in educational quality, we presume that there are multiple other factors affecting the grades during COVID-19. Hence, we have identified five potential explanations that might correlate with people's lives during the COVID-19 pandemic and students' academic performance. By exploring these possible explanations, we can disentangle some effects of online education on student grades and facilitate an understanding of why the impact of online education on student grades at LUSEM might point in a specific direction.

Our study will highlight the following mechanisms: cheating, teacher effect, peer effects, mental health and motivation, and time allocation. The reason for choosing those five mechanisms is based on both previous literature and empirical findings. We will address those explanations by presenting relevant economic theories and empirical evidence linked to these mechanisms. Further, we will apply and contextualize these economic theories on our results in the discussion section. Although these five explanations are insufficient for explaining all possible mechanisms that might drive changed grades during online education, they provide a basis for understanding some reasons why grades have changed in a specific direction. Thus, we acknowledge the possibility of other channels affecting student grades. Nevertheless, we stress the importance of highlighting these five to come closer to an understanding of the link between online education and grades.

2.2.1 Cheating

The economics of crime framework was introduced by Becker (1968), who addressed several economic dimensions of criminal behavior. For example, this framework highlights impacts on different incentives behind criminal behavior and potential ways to predict and find explanations for why crimes occur. Furthermore, Becker (1968) stresses that one essential factor in explaining the number of criminal actions that are taken place is the probability of being caught. From the theory of Becker (1968), the individual compares the gains that come from committing the crime with the gains from not committing the crime. Moreover, if the gains from committing a crime are higher than those from not committing the crime, the rational choice for the individual will be to take the criminal action. Therefore, an individual will commit a crime if taking the crime is the most attractive alternative present.

The model of Becker (1968) can be applied to different kinds of crimes, such as cheating on an examination. Hence, applying the model to our study, we assume that the probability of being caught cheating have decreased during online examination compared to during supervised examinations on campus. Consequently, the reduced likelihood of being caught cheating leads to increased cheating levels during online examinations. The higher degree of cheating is also in line with data from Swedish Universities Disciplinary Committee. This authority is allowed to take actions, such as expelling and warning students if a student is caught cheating. Such actions are called disciplinary matters and have, according to Swedish Universities Disciplinary Committee (2022) increased during 2020 and 2021. Since the increased number of disciplinary matters correlates with the inclusion of more online examinations during the COVID-19 pandemic, it is reasonable to assume that the increase in disciplinary matters partly stems from increased cheating during online examinations.

Applying this empirical evidence from Swedish Universities Disciplinary Committee (2022) to our study, growth in the cases of cheating might indicate that a part of the explanation for higher grades is that students cheat to a greater extent. However, it is not easy to examine this mechanism with certainty. Firstly, Swedish Universities Disciplinary Committee (2022) only has data on cheating on an aggregated level, making it impossible to link student grades with increased levels of cheating. Secondly, there might be high levels of dark figures on cheating due to the possible consequences of being honest.

2.2.2 Teacher Effect

In the process of education, one crucial input for students learning and grades is the teacher. Therefore, to understand the impact of online education, one has to consider how teachers have coped with the online setting. There are undoubtedly multiple aspects to consider to understand the role of the teachers during the COVID-19 pandemic. For example, how well the teachers have responded to the increased requirements of technological skills and how fast they have adapted to the new learning environment. However, it is also important to understand possible mechanisms behind how teachers have graded examinations during these precarious circumstances. Therefore, this chapter will focus on two potential channels linked to the teachers' grading strategy: (a) decreased generosity when evaluating students due to increased social distancing, and (b) increased generosity when evaluating students due to the feeling of needing to compensate for the poor conditions.

Decreased generosity due to social distancing
In standard economic theory, all individuals are assumed to act out of pure self-interest and maximize their utility (Jehle & Reny 2011). A Dictator Game is commonly used as an experimental design to test whether individuals act out of pure self-interest in reality. The setup in the Dictator Game is as follows: the Dictator receives a fixed amount of money. After that, the Dictator can decide how much money to keep and how much to give away. According to standard economic theory, the most rational choice of the Dictator is to keep all money and give away nothing to its counterpart. In standard economic theory, the Dictator should, in a rational manner, keep all the money and give away nothing to its counterpart. However, several studies such as Hoffman et al. (1996), Bohnet & Frey (1999) have shown that the Dictator usually gives away more than the theory predicts, i.e., more than zero.

Another dimension that both Bohnet & Frey (1999) and Hoffman et al. (1996) add to the Dictator Game theory is that the degree of social distance also is crucial for determining how much the Dictator will give away to the other player. For example, in Bohnet & Frey (1999), they find that the Dictator gives away on average 26% of the money when the identity of the counterpart is anonymous. Moreover, they also find that this amount increases to 35% when the Dictator can observe the counterpart's identity. The Dictator gives away the most money when both players can observe each other, giving away 52% of the money to the other player. These results suggest that the predictions from the economic theory of maximizing one's own utility (Jehle & Reny 2011), might not be completely applicable in reality since individuals might not behave purely rationally.

Based on the findings by Bohnet & Frey (1999), and Hoffman et al. (1996), there seems to be a link between generosity and social distance. The main results from both studies are that when distance increases, generosity also decreases. Applying the findings on social distance and generosity to teachers' situation at LUSEM during online education, we assume that increased social distance might have contributed to less generous grading. For example, if only observing the students in an online classroom, there might be a more considerable distance between the students and teachers than in a typical on-campus setting. Such a distance might be even larger in courses with a high number of students, where students might not have their cameras on in the online classes.

Compensating behavior and social justice
The teachers' generosity could also point toward a more positive direction. For example, the teachers might have experienced an intensified urge to compensate the students for the poor circumstances of online education during COVID-19 (Karadag 2021). Furthermore, Konow (2003) conducts a profound investigation of justice theories and highlights multiple theories and perspectives on social justice. For example, Konow (2003) emphasizes the theory of equal opportunities, which has the primary goal is to create an environment with equal possibilities for individuals. Hence, the main objective is not to equalize outcomes but to equalize opportunities for individuals. Moreover, Konow (2003) underlines that the essence of the theory is to compensate people for factors that are not under their control.

Furthermore, Konow (2003) stresses that equality of opportunity usually implies allocating resources in such a way that favors disadvantaged people the most. Konow (2003) links the theory on equality of opportunity to Roemer (1998), who developed a metaphor about equalizing resources by "level the playing field" for individuals. Level the playing field refers to an environment in which everyone can have an equal chance of succeeding, thus equalizing the opportunities for individuals.

If applying the equality of opportunity theory by Konow (2003) and the aspect of "level the playing field" between individuals to equalize opportunities, one can argue that teachers during the COVID-19 pandemic might have been more generous in their grading due to external consequences. Suppose teachers have felt that the opportunities for student cohorts have differed before and after online education during the COVID-19 pandemic. In that case, the teachers might have been eager to compensate students' poor circumstances during online education with higher grades to equalize the opportunities between student cohorts at LUSEM.

2.2.3 Peer Effects

Peer effects refer to interaction with other peers that impacts a person's learning, such as how the interplay between students during an educational process affects students learning (Zimmerman & Winston 2004). Since peer effects refer to when spillovers in learning are generated, peer effects imply that having high achieving peers may enhance one's learning outcomes. Accordingly, a class with high-achieving students will generate positive spillovers and enhance other students learning process. Similarly, having low achieving peers might hamper one's learning process.

Furthermore, Zimmerman & Winston (2004) highlight some of the difficulties of measuring the presence of peer effects. For example, two difficulties linked to measuring peer effects are: deciding what peer attributes to observe and the issue of selection bias when measuring peer effects between students. The selection bias is due to people choosing their peers to a large extent and accompanying people with similar characteristics. Thus, high-achieving students tend to be drawn to environments with other high-achieving students, making it difficult to isolate if high grades are driven by peer effects or selection bias.

In a study by Zimmerman & Winston (2004), they estimate peer effects by exploiting roommate assignment. They argue that estimating peer effects and roommate assignment overcome selection bias in higher education. Moreover, they argue that this method is close to random selection for first-year students at certain schools. Furthermore, Zimmerman & Winston (2004) use data on educational outcomes such as individual student's grade, Scholastic Aptitude Test (SAT) scores, and their roommate's SAT scores to examine how the roommates' academic traits affect individual's grade. The findings of Zimmerman & Winston (2004) suggest that the grade of students in the upper quartile of the SAT distribution tend not to be affected by the SAT score of their roommate. If the student is in the middle of the SAT distribution, the effect on grade tends to be negative if their roommate is in the lower quartile of the SAT distribution.

Similarly to Zimmerman & Winston (2004), Zimmerman (2003) and Sacerdote (2001) also made a pairwise comparison of students' and their roommates' educational outcomes. Zimmerman (2003) argues that individuals in the middle of the SAT distribution can be negatively affected if their peers are academically weak, and Sacerdote (2001) suggests that students that share a room with remarkably academically strong tend to gain higher grades.

Although the findings of Zimmerman & Winston (2004), Zimmerman (2003), Sacerdote (2001) provide important insights into how peer effects might impact student outcomes, they all explore this link in an on-campus environment. However, none of the papers above have analyzed peer effects in a situation with online education as the primary teaching method. The effects could be twofold in the context of students' situation at LUSEM during the COVID-19 pandemic. The peer effect might have decreased during online education since students have spent less time on-campus studying with their peers. In that case, the peer effects might be smaller during online education than during times with purely on-campus education. On the other hand, the peer effects might be larger during social distancing. For example, more substantial peer effects could occur if roommates spend substantially more time together and are isolated from other people. In such a case, roommates might affect each other's learning process even more, although we do not know which direction.

Nevertheless, studies such as Bettinger et al. (2016) suggest that peer effects are not only an exclusive on-campus phenomenon. In the study, Bettinger et al. (2016) examine data from an online college course to evaluate student outcomes and their level of persistence within higher education. Their results suggest that older students, and especially female students, are more likely to participate in student interactions. Also, their results imply that students are more likely to participate in discussions with other students of the same gender. Interestingly, they find that students exposed to more interactive peers during online education will have an increased chance of passing the course. Additionally, being exposed to more interactive peers will also increase the likelihood of other students getting higher grades and enrolling in the subsequent academic term. Thus, the existence of peer effects during online courses implies that the course layout and inclusiveness of elements, such as break-out rooms, might create different conditions from spillovers between peers (Bettinger et al. 2016).

Based on the results from Zimmerman & Winston (2004), Zimmerman (2003), Sacerdote (2001), we acknowledge the existence of peer effects in the case of education at LUSEM. However, we cannot be sure how the peer effects might have changed during online education or about their magnitude. Although previous findings, such as Bettinger et al. (2016) find that peer effects are present during online education, we suppose that the peer effects are more significant during on-campus education than in online education, assuming that in-person interactions are more determining than online interactions.

2.2.4 Mental Health and Motivation

Previous studies show evidence for a negative correlation between mental health problems and academic achievement, which indicates that if, for example, a student has an increase in mental health problems, this may harm their educational performance (Jeffries & Salzer 2021, Puskar & Bernardo 2007, Gujare & Tiwari 2016). The outbreak of the coronavirus and associated restrictions have had implications on people's, including students, day-to-day life. Due to the magnitude of the coronavirus spread and its unprecedented effects on individuals' routines, several studies have been made to understand the implications of the pandemic on people's mental health and well-being. For example, McCracken et al. (2020) conduct one such study and examine the impact of the COVID-19 pandemic on the mental health and well-being of the Swedish population two and a half months after the first appearance of COVID-19 in January 2020.

By conducting correlation analyses, McCracken et al. (2020) estimate what factors correlate with mental illness, such as depression, anxiety, and insomnia. Moreover, McCracken et al. (2020) found that factors such as age, income, and education were negatively correlated with the mental health measures. Furthermore, the negative association between age and mental illness measures suggests that older people experienced less psychological distress than younger people during the COVID-19 pandemic. Most importantly, they also find a positive correlation between these mental health issues and being a student. This result suggests that students at LUSEM also may have experienced negative impacts on their mental health problems during the COVID-19 pandemic.

Likewise, Browning, Larson, Sharaievska, Rigolon, McAnirlin, Mullenbach, Cloutier, Vu, Thomsen, Reigner, Metcalf, D'Antonio, Helbich, Bratman & Alvarez (2021) identify college students as a vulnerable group due to relatively high degrees of anxiety, depression, substance abuse, and lack of self-esteem compared to the general population before the pandemic. Hence, Browning et al. (2021) assumes that these mental health issues have intensified during COVID-19 and its subsequent measures, such as social distancing. For example, students have been affected by uncertainty regarding their educational setting, future work career, and social interactions. By using survey data from students at seven different universities in the United States, Browning et al. (2021) find evidence that student experiences considerable changes in their day-to-day lifestyle. Some behaviors that significantly had changed due to the pandemic and related measures for students were going out less, more social distancing, isolation, and changes in educational form. Additionally, students' psychological health factors have also changed during the pandemic. For example, students have, according to Browning et al. (2021) experienced a lack of motivation, increased anxiety, and higher stress levels during the COVID-19 pandemic.

The results presented by Browning et al. (2021) are in line with previous literature finding negative impacts for students during the COVID-19 pandemic, such as an increased feeling of anxiety, stress, and uncertainty about their education and future employment (see, e.g., Aristovnik et al. 2020, Chen et al. 2020, Elharake et al. 2022). For example, Aristovnik et al. (2020) highlight negative feelings due to increased social distancing and being far from home, which might affect their schooling negatively. Moreover, studies such as Huckins et al. (2020) have seen growth in anxiety, depressive symptoms, and more inactive lifestyles for university students in the United States.

Additionally, empirical evidence suggests that students have experienced more mental health issues during online education at LUSEM. The negative impact on mental health is demonstrated by the survey study by LundaEkonomerna for the Speak Up Days, suggesting that students feel worse during the COVID-19 pandemic and related online education. For example, almost 50% of the students surveying the Speak Up Days answered that online learning had affected their mental health in a negative way (LundaEkonomerna 2020).

2.2.5 Time Allocation

A profound concept in microeconomic theory is the opportunity cost, referring to the value lost when selecting an option over an alternative option. The opportunity cost is simply the value of the lost opportunities when making a specific choice, thus incorporating the trade-off associated with making specific choices (Cowen & Tabarrok 2021). During the COVID-19 pandemic, students' alternatives to studying have significantly dropped. For example, student clubs and associations have been closed, canceled parties, and postponed sports events. Due to these decreased options for students to spend a day in their life, one natural consequence of the COVID-19 pandemic is simply a decreased opportunity cost of studying. The value lost when studying (i.e., the opportunity cost of studying) increases when there are many other options on things to do. Therefore, it gets more costly (in terms of opportunity costs) to study when there are options such as being active in student clubs, parties, and sports event that attracts students.

Based on this theory, the COVID-19 pandemic and subsequent closures of clubs, sports events, and other activities might have resulted in more studying time. In theory, this could be a consequence of the decreased opportunity cost of studying during the pandemic, when many activities included in the "normal" student life have decreased. However, it is uncertain whether the freed time is devoted to more studying. Still, empirical evidence from LundaEkonomerna (2020) shows that students spend slightly more time studying after the COVID-19 pandemic compared to before. However, it remains unclear whether this increased time spent studying is due to a change in the opportunity cost of studying or whether the increased study hours stem from, for example, more obstacles in the learning process. Nevertheless, it is still essential to consider the time aspect in the analysis.

Information obtained from LundaEkonomerna (2020) also showed that master's students allocate more of their time to school in general, despite being a pandemic or not than undergraduate students. The reason could be more advanced courses and a more extensive workload; they are further ahead in their career and thus may be more focused on the future, or are people with higher ability (Becker 1962). Also, this assumption is supported by information regarding members from LundaEkonomerna Student Union, where the active members in the student association consist mainly of undergraduate students.

2.2.6 Summary of Explanations

In Table 2, we present our potential explanations and state what direction we expect the mechanisms to work. As shown in Table 2, we expect either a negative or positive impact or that the positive and negative effects might outplay each other.

Table 2: Summary of Possible Explanations

Explanation	**Expected Direction**
Cheating	+
Teacher Effect	+/−
Peer Effects	−
Mental Health and Motivation	−
Time Allocation	+/−

3 Institutional Framework

3.1 Lund Unversity School of Economics and Management

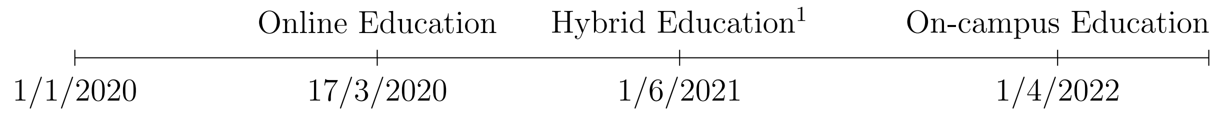
Lund University School of Economics and Management (LUSEM) is one of nine faculties at Lund University. Lund University and LUSEM finance their organization through government money and other types of funding (Lund University of School of Economics and Management 2021). At Lund University, there are, in total, approximately 46 000 students, divided by its three campuses in Helsingborg, Malmö, and Lund (Lund University 2022*a*). At LUSEM specifically, there are approximately 4000 students and over 300 researchers. LUSEM conducts research and education in business administration, economics, economic history, business law, informatics, statistics, and research policy.

LUSEM is accredited by AACSB, AMBA, and EQUIS, implying that the research conducted at LUSEM holds a high international quality standard (Lund University of School of Economics and Management 2022). Furthermore, Lund Unversity (LUSEM included) uses the Ladok-system for reporting and documenting student results. Ladok's local register includes information regarding students' results at Lund University at all levels (Lund University 2022*b*).

3.2 Timeline

Lund University has been following the recommendations provided by the Swedish Government throughout. Accordingly, we will use the dates for the recommendations from the Swedish Government as determinants for treatment status. The timeline below illustrates the important dates for when LUSEM has switched from on-campus to online education and vice versa. As depicted on the timeline, the first relevant date is the 17th of March in 2020, which is the date when the Government of Sweden announced the recommendation that universities switch from on-campus to online education because of the spread of the coronavirus (Public Health Agency of Sweden 2020). LUSEM switched to online education the next day; thus, the first day of online education was the 18th of March.

During the rest of 2020 and until the beginning of June 2021, the Public Health Agency of Sweden continued to recommend that universities keep their education online. However, on the 1st of June 2021, they announced the recommendation that universities instead could have parts of the education on-campus, but still with several recommendations such as keeping social distance. After the 1st of June 2021, most universities maintained online education combined with some on-campus education. Hence, the period between the 1st June 2021 and 1st April 2022 included a combination of online and on-campus learning (Government Offices of Sweden 2022). According to the fact that universities in reality combined online and on-campus education, we will refer to this period as hybrid. The examinations occurring after the 1st June 2021 coincide with the hybrid period for education at LUSEM. However, the examinations in June and August were conducted before LUSEM allowed students back on campus, meaning that these examinations were unaffected by the hybrid mode in reality, and we will, therefore, include the examinations conducted in June and August 2021 in our treatment period for online education.



[1] Although the recommendations from the Public Health Authority allowed on-campus education in theory, there were many premises and advice that made it difficult for universities to have the education on-campus. Thus, in reality, the education was conducted through a combination of online and on-campus education in a "hybrid" mode (The Government Offices of Sweden 2022).

4 Data

To examine the impact of online education on student grades at LUSEM, we have obtained data from Ladok, the national system for student grades used by many higher education systems in Sweden. Additionally, Ladok is also from where The Swedish Board of Student Finance (CSN) collects its information (The Swedish Board of Student Finance 2015). The data on student grades covers the period from 16th January 2017 to 29th August 2021, when the education was either purely on-campus or purely online.

The pre-treatment period is all dates before or on 17th March 2020, and the post-treatment period corresponds to all observations after 17th March 2020 in our sample. From 30th August 2021[2] the education at LUSEM adopted a hybrid form that lasted into the spring term of 2022. We do not have sufficient information regarding the hybrid period to analyze this accurately. Since, for example, some courses were held entirely online, some had certain elements on-campus, and some had entirely gone back to in-person learning. Even though it would have been interesting to examine this hybrid period, we are constrained by course-specific data. Therefore, we have limited our research to focus on the potential differential impacts between campus education and online education.

We have merged data from the Department of Economics, our primary focus area, with data from the Department of Business Administration, Department of Economic History, Department of Statistics, and Department of Business Law. We have acquired data on all courses from the Department of Economics and data from introductory courses in the four other departments. In addition, we have data on the intermediate courses in Business Administration and Statistics. Combining observations from these different departments allows us to examine the student grades from a broad range of courses at LUSEM.

Initially, the sample consisted of 172 courses. However, throughout the data process, we excluded all courses with a frequency of fewer than 50 student observations. Secondly, we kept courses with the grading scale UA (i.e., A, B, C, D, E, and U) and omitted other grading systems, such as UG, UV, and TH. However, the UG scale consists of only two grades: G and U, i.e., passed and failed, TH ranges from 5 to 3, and UV ranges from VG to U. The reason why excluding the UG scale is that most of those grades are based on student grades on assignments. Furthermore, the reason behind excluding the TH and UV is the relatively low frequency of those scales. Also, limiting the sample to one scale makes it easier to compare the outcomes in different courses. The combined data set captures as many as 65 408 individual students' grades, 73 courses, and 1 611 examination opportunities.

[2] The spring term formally ended 6th June at LUSEM 2021, but the students having their examinations during the summer have been considered part of the online education instead. This is because they have been considered unaffected by the transition to hybrid education.

4.1 Outcome Variable

In Table 3 the definitions and descriptions of all variables are presented. To examine the impact of online education on student outcomes, we investigate students' grades obtained from a particular course examination. The passing grades range from A to E, where A is the highest and E is the lowest. U represents the failing grades.

Moreover, we have re-coded the grades to an ordinal scale:

- A corresponds to 5.
- B corresponds to 4.
- C corresponds to 3.
- D corresponds to 2.
- E corresponds to 1.
- U corresponds to 0.

We have access to passing and failing grades from the Departments of Economics, while in the remaining departments, we have only data on passing grades. Therefore, when we compare across departments, we exclude the failing grades from the Department of Economics. Hence, failing grade U is only included when analyzing courses at the Department of Economics. Furthermore, the most frequent grade at the Department of Economics is the failing grade U. The reason why the grade U is the most common might be because students can only pass a course once but can, in theory, fail a course an unlimited number of times. Additionally, a student can choose not to take a re-exam in a course, and therefore some of the failing grades will never have a corresponding passing grade.

Although we have access to individual-level data covering grades for 65 408 students, we have no possibility of examining individuals over time due to regulations on individual identities. Thus, the data shows us individual grade outcomes but not any other type of identification of the individual[3]. Therefore, one of our approaches is to investigate student grades at an aggregated level. Hence, we will use the average grades at each examination in a course to compare the impacts of on-campus education and online education in some estimations. Still, where feasible, we will exploit the raw data on an individual level. For example, we will use the individual-level data to present our descriptive statistics and when testing the samples' distributions in Wilcoxon rank-sum test.

[3]This is due to security aspects and the fact that Ladok stripped the identities for the students.

4.2 Explanatory Variables

As shown in Table 3, the majority of the explanatory variables are dummies, taking either value 1 or 0 depending on status. Our main explanatory variable is $POST$, a dummy for the treatment period, taking the value 1 if the date occurs during online education (18th March 2020 - 31st August 2021) and 0 otherwise (18th January 2017 - 17th March 2020). $NEKA12$ represents the introductory course in economics. This variable is utilized in our Difference-in-Difference approach, where we compare the introductory course online NEKKPA and on-campus NEKA12. $TERM$ estimate whether there is a trend in student grades over time, starting at the value 1 if it is the spring semester of 2017 and stretching to the value 5 if it is the spring semester of 2021. A negative coefficient of $TERM$ suggests that grades tend to decrease over time, while a positive coefficient indicates grades have an increasing trend. The dummy variable $GENDER$ takes the value 1 if it is a female student and 0 if a male student.

Furthermore, the variable $MATH$ indicates whether the course is quantitative or not. All mathematical and econometric courses obtain the value 1 and 0 otherwise. We include both mathematics and econometrics courses in the definition of mathematical courses. Econometrics has been included in $MATH$ since it is also very quantitative. Furthermore, the variable $ESSAY$ takes the value 1 if it is an essay course and 0 otherwise. The dummy variable $MASTER$ indicates whether the course is at undergraduate or master's level. Hence, $MASTER$ takes the value of 1 if the course is a master's level and 0 if it is at the undergraduate level.

Lastly, the remaining dummy variables demonstrate to what department the course belongs. The departments included in the sample are the vast majority of departments at LUSEM, only excluding the Department of Informatics. The explanatory variable $ECON$ includes data from the Department of Economics, BUS from the Department of Business Administration, HIS from the Department of Economic History, $STAT$ from the Department of Statistics, and LAW from the Department of Business Law.

Table 3: List of Variables

Outcome Variable	**Description**
GRADE	Ordinal variable ranging from 0 to 5. A=5, B=4, C=3, D=2, E=1, and U=0.
Explanatory Variable	
POST	Treatment period. Dummy variable equaling 1 for the period of online education, 0 otherwise.
NEKA12	Treatment group. Dummy variable equaling 1 for course exposed to transition to online education, 0 otherwise.
TERM	Time trend variable of spring terms. 2017 = 1, 2018 = 2, 2019 = 3, 2020 = 4, and 2021 = 5.
GENDER	Dummy variable equaling 1 if the student is female, 0 if male.
MATH	Dummy variable equaling 1 if course is a mathematical or econometric course, 0 otherwise.
ESSAY	Dummy variable equaling 1 if examination form is essay, 0 otherwise.
UNDERGRADUATE	Dummy variable equaling 1 if course is at undergraduate level, 0 otherwise.
MASTER	Dummy variable equaling 1 if course is at master's level, 0 if undergraduate level.
SUMMER	Dummy variable equaling 1 if the exam is taking place in the summer, 0 otherwise.
FALL	Dummy variable equaling 1 if the exam is taking place in the fall, 0 otherwise.
ECON	Dummy variable equaling 1 if course is at the Department of Economics, 0 otherwise.
BUS	Dummy variable equaling 1 if course is at the Department of Business Administration, 0 otherwise.
HIS	Dummy variable equaling 1 if course is at the Department of Economic History, 0 otherwise.
STAT	Dummy variable equaling 1 if course is at the Department of Statistics, 0 otherwise.
LAW	Dummy variable equaling 1 if course is at the Department of Business Law, 0 otherwise.

5 Methodological Framework

We use four different methods: Wilcoxon rank-sum test, Ordinary Least Squares, Differences-in-Differences, and Regression Discontinuity Design. This combination of methods allows us to capture several impacts of online education on grades and optimize how our data is structured. For example, when evaluating descriptive statistics and Wilcoxon rank-sum test, we can take advantage of our individual-level data. Additionally, when making our OLS regressions and Difference-in-Difference estimations, we can adjust our sample of courses to test specific effects.

5.1 Wilcoxon Rank-Sum Test

Due to the high frequency of the grade U, compared to the other grades between A to E, our data does not follow a normal distribution; thus, our data violates the requirements for a parametric test. Consequently, we use a non-parametric test since it does not make an assumption regarding underlying distributions and is, therefore, more suitable for our data. Accordingly, we use a Wilcoxon rank-sum test, a non-parametric counterpart to the parametric two-sample t-test. The test was developed by Wilcoxon (1945), who introduced two non-parametric methods: Wilcoxon rank-sum test and Wilcoxon signed-rank test. The two approaches exploit ranking methods and have a common purpose, but the tests differ when it comes to their application. The rank-sum test is used when the groups are unpaired and independent of each other, while the signed-rank test is applied when the two samples are paired and related to one another. However, we cannot follow specific students across courses and terms; thus, we cannot match the data pairwise across the two groups. Therefore, we use the rank-sum test instead of the signed-rank test.

The Wilcoxon rank-sum test, which is similar to the Mann Whitney U test (Mann & Whitney 1947), compares the distributions of two groups and tests whether the two samples have the same distribution or if one is stochastically larger than the other. Hence, the hypotheses are:

$$H_0 : \text{population distributions are equal}$$

$$H_1 : \text{population distributions are not equal}$$

Since we only compare the distributions of the two groups and do not control for any other factors, we use data on an individual level, which provides a raw test on the data. Furthermore, we will conduct comparisons between the two teaching modes in four different samples:

- *Panel A*: All grades at the Department of Economics
- *Panel B*: Passing grades at the Department of Economics

- *Panel C*: Passing grades at the Department of Business Administration, Department of Economic History, Department of Statistics, and Department of Business Law
- *Panel D*: Passing grades at the Department of Economics, Department of Business Administration, Department of Economic History, Department of Statistics, and Department of Business Law

Moreover, we will limit the sample in some cases, for example, solely looking at the effect on a particular gender or the quantitative courses.

5.2 Ordinary Least Squares

An Ordinary Least Squares (OLS) regression will be applied to our data to investigate the effect of online education on grades. Although our dataset consists of repeated observations for the same individuals, we have no possibility of identifying individual variation. Thus, we cannot exploit variation on an individual level in the OLS estimations. Instead, we use group-level variation and examine the variation within courses. Hence, one observation will consist of the average grade on a particular examination. Using course fixed effects, we can take constant differences in grades across courses into account. For example, we can control for quantitative courses always tending to generate higher grades than non-quantitative courses (Angrist & Pischke 2009).

Furthermore, we use clustered standard error on a course level since our treatment assignment may be correlated within groups. Clustering on a course level rather than a module level generates larger groups and results in fewer clusters. Hence fewer clusters are preferable since it means less independent data in the sample (Angrist & Pischke 2009). We have executed several tests to check if our data and model fulfill the assumptions of an OLS regression. The variables $MASTER$ and $ESSAY$ had a slight tendency to be correlated when conducting the test for multicollinearity. However, none of these two are our variables of primary interest and are only included simultaneously in two regressions. Therefore, multicollinearity should not be a problem for our OLS regressions. Besides multicollinearity, the test results validate the robustness of our model, and thus, an OLS regression is feasible in this setting.

5.2.1 Evaluating the General Impact of Online Education on Grades

We have compared the general effects of online education in all courses at the Departments of Economics[4] for the entire sample period. The results of the regressions are demonstrated in Table 7. The specification for the OLS regression used to examine this

[4] All courses except NEKKPA are included in the sample since NEKKPA is an online course and is thus never affected by the transition to online education.

relationship is established in the following way:

$$\begin{aligned} GRADE_{it} = \beta_0 + \beta_1 POST_{it} + \beta_2 TERM_{it} + \beta_3 GENDER_{it} + \beta_4 MATH_{it} + \\ \beta_5 ESSAY_{it} + \beta_6 MASTER_{it} + \beta_7 FALL_{it} + \beta_8 SUMMER_{it} + \epsilon_{it} \end{aligned} \tag{1}$$

In the equation, $POST$ show the general impact of shifting from on campus education to online education; $TERM$ captures a potential time trend in grades; $GENDER$, $MATH$, $ESSAY$, $MASTER$, $FALL$, and $SUMMER$ are all dummy variables and control variables; ϵ is the clustered standard errors.

Additionally, we have compared the outcomes at different departments at LUSEM by using OLS regressions, which results can be seen in Table 7. When we analyze the effects in other departments at LUSEM besides the Department of Economics, our data is limited to passing grades at the undergraduate level. Therefore, we cannot investigate the impact on math courses, essay courses, or master's students. The specification for the OLS regressions that have been used to examine the effect on student grades of online education across different departments become the following:

$$\begin{aligned} GRADE_{it} = \beta_0 + \beta_1 POST_{it} + \beta_2 TERM_{it} + \beta_3 GENDER_{it} + \beta_4 FALL_{it} + \\ \beta_5 SUMMER_{it} + \beta_6 BUS_{it} + \beta_7 STAT_{it} + \beta_8 HIST_{it} + \beta_9 LAWit + \epsilon_{it} \end{aligned} \tag{2}$$

Similarly to Equation 1, $POST$ illustrate the effect of online education; $TERM$ demonstrate a trend in grading over time; $GENDER$, $FALL$, and $SUMMER$ are all dummy variables and control variables. BUS represents the effect for courses within the Department of Business Administration; HIS within the Department of Economic History; $STAT$ within the Department of Statistics; LAW represents the effect for courses within the Department of Business Law. ϵ is the clustered standard error.

5.2.2 Evaluating the Impact of Online Examination on Grades

To isolate the effect of having an examination online examination compared to on-campus, we exploit that the switch to online education happened in the middle of an examination period. Consequently, some students had all lectures on-campus but the examination online in the spring of 2020. We explore the impact of the examination form on student grades by using data from examinations between the 18th of March and the 4th of April 2020. As a control group, we use the corresponding examinations in the spring terms of 2017, 2018, and 2019. Thus, by focusing on examinations within this period, we capture the impact of online examinations on student grades.

We will use the same specification shown in Equation 1, but another sample of courses since we restrict the period of examinations. Consequently, the dummy variables $ESSAY$ and $FALL$ are excluded. Similar to in Equation 1, we use course fixed effects and clustered standard error at the course level. The results of these OLS specifications are demonstrated in Table 8. So, the specification in this case is:

$$\begin{aligned} GRADE_{it} = \beta_0 + \beta_1 POST_{it} + \beta_2 TERM_{it} + \beta_3 GENDER_{it} + \\ \beta_4 MATH_{it} + \beta_5 MASTER_{it} + \beta_6 SUMMER_{it} + \epsilon_{it} \end{aligned} \tag{3}$$

Likewise to Equation 1 and 2, $POST$ shows the impact of online education; $TERM$ portrays a potential time trend in grades; $GENDER$, $MATH$, $MASTER$, and $SUMMER$ are all dummy variables and control variables; ϵ is the clustered standard errors.

5.3 Differences-in-Differences

Likewise to the OLS estimations, we cannot use the individual-level variation in the DiD estimations. Therefore, we use the average grade at each examination, thus exploring the variation on an aggregated level. The DiD framework estimates the effect of a particular treatment by comparing the outcomes for the treated group with the outcomes for a similar but untreated control group. The treatment group is exposed to the treatment, while the control group is similar to the treatment group but not exposed and affected by the treatment. By comparing the differences in outcome within and between the courses, it is plausible to isolate the treatment effect of online education[5](Angrist & Pischke 2009).

We utilize the fact that we have one course that is always online and a correspondent course that is usually never online. Thus, we compare the grades of NEKKPA, which is unaffected by the shift in education form, to NEKA12, which is affected by the change of education form. NEKKPA is the online introductory course in economics and is always online regardless of whether it is a pandemic or not, while NEKA12 is the on-campus introductory course in economics and is usually only taught on-campus in a non-pandemic setting. Besides different teaching modes, these courses are equivalent in content, have four modules, and are taught once every semester. Since NEKKPA never switches teaching mode and ought to be unaffected education-wise, it operates as a control group. Contrarily, NEKA12 is the treatment group since it shifts from on-campus education to online education after the 17th of March.

Accordingly, we estimate the impact of online education on grades by comparing NEKA12, which has changed from on-campus education to online education, with NEKKPA, which always has online education. All of the above boils down to the following equation:

$$\begin{aligned} GRADE_{it} = \beta_0 + \beta_1 POST_t + \beta_2 NEKA12_i + \beta_3 (POST_t \cdot NEKA12_i) + \\ \beta_4 GENDER_{it} + \beta_5 FALL_{it} + \beta_6 SUMMER_{it} + \epsilon_{it} \end{aligned} \tag{4}$$

In the equation, $POST$ is a dummy showing the effect for time t; $NEKA12$ is a

[5] See Appendix for derivation.

dummy taking demonstrating the effects for examination i; and the interaction term $(POST \cdot NEKA12)$ is the Difference-in-Difference estimator capturing the examinations after 17th of March 2020, i.e., when the course shifted to online education. Furthermore, the variables $GENDER$, $FALL$, and $SUMMER$ are our control variables, and ϵ is the clustered standard error term for the estimation.

5.4 Regression Discontinuity Design

Another methodological approach we have applied is the Regression Discontinuity Design (RDD). The RDD exists in two versions: fuzzy and sharp. A fuzzy RDD is used when the assignment rule of treatment is probabilistic, indicating that the probability of treatment increases at the cut-off, but it does not necessarily have to be a jump from 0 to 1. The sharp RDD is applied when the treatment status is deterministic, thus when the probability of treatment switches from 0 to 1 at the cut-off point. Therefore, an assumption for sharp RDD is that there is a discontinuity from 0 to 1 in the probability of being exposed to a specific treatment at the assigned cut-off point. Hence, the cut-off point x_0 must determine the treatment status of x_i (Angrist & Pischke 2009). In our case, this discontinuity occurred on the 17th of March 2020, when LUSEM changed to online education following recommendations by the Swedish Government, which constitutes a sharp cut-off point.

Technically, a sharp RDD can be illustrated as below:

$$D_i = \begin{cases} 1 & \text{if } x_i \geq x_0 \\ 0 & \text{if } x_i < x_0 \end{cases} \tag{5}$$

Where x_0 is the cut-off point at which D_i changes treatment status. The reason why this function is discontinuous and deterministic is that x_i entirely determines what D_i is. Therefore, the function is discontinuous since the treatment will not be changed until x_i reaches the cut-off point. Thus, the treatment status will change where x_i is equal to x_0, which leads to $D_i = 1$ (Angrist & Pischke 2009). In our study, x_0 is the 17th of March 2020, and x_i is the date of examination i. Thus, all examinations occurring on or before the 17th of March have on-campus education ($D_i = 0$), while all examinations after the 17th of March are assigned the treatment status of online education ($D_i = 1$). The results from the RDD are shown graphically with a quadratic best-fitted line in Figure 1 to Figure 6.

5.5 Limitations to methodological framework

Combining the four methods makes it possible for us to capture multiple nuances of the impact of online education on grades. However, there are some potential concerns and limitations regarding our methodological approach. One such issue is that we have individual-level data but no information regarding identity. Consequently, we can not control individual variation. Therefore, we apply course-fixed effects to our regressions and thereby control for observed and unobserved time-invariant factors across different courses, allowing us to account that students might always perform better in courses like essays or quantitative. Therefore, although we cannot follow the same individuals over time, we can examine the impact on grades at a more "micro" level by applying course-fixed effects. It would have been a more profound analysis if we could follow individuals over time. However, we still have enough information to provide a firm and solid investigation of how online education has impacted student grades.

Furthermore, we do not have data on other factors, such as mental health problems, teacher, set-up of examination, or course layout, that might affect students' grades. Accordingly, the estimations might suffer from omitted variable bias due to the impossibility of including such factors in our estimations. However, accounting for all potential factors that impact student grades would have required extensive work and data access that would require more time than this study provides.

Lastly, our sample consists only of students at LUSEM, which may be considered a relatively homogeneous group. Thus, our sample of students may not represent the whole population and risk violating the assumption of random selection. Consequently, in some other settings, the external validity could be questioned since the findings of this paper might not be applicable to vastly different settings. However, the results could still apply to similar settings at other universities, for example, at other Business and Economics departments. Therefore, the outcomes of this study are still policy-relevant and essential for designing educational policies in Sweden, but possibly also in countries with similarly organized universities and business schools.

6 Results

6.1 Descriptive Statistics

Table 4 shows descriptive statistics for student grades in the Department of Economics for different groups[6]. In Panel A in Table 4, the mean, median, standard deviation, the number of individual observations, and the percentage difference in the average grade are shown for failing and passing grades. In Panel B, only passing grades are included in

[6]See Appendix for summary statistics on an examination level.

the descriptive statistics. Moreover, we calculate the percentage differences between the pre-treatment and post-treatment periods.

Furthermore, Panel A shows that the average grade is approximately 2.33 for all students in the Department of Economics in the pre-treatment period. For all students, there has been a decrease in grades by -5.6% to 2.20 in the post-treatment period. However, the average grade for female students has dropped from 2.30 to 2.17, corresponding to a decrease by -5.7%. Additionally, for male students, the decrease has been -5.1%, since the average grades have declined from 2.35 to 2.23.

When narrowing the sample to only math courses, the average grades are slightly higher than the general average for all students and courses, with an average of 2.91 in the pre-treatment period. In the post-treatment period, the math grades increased from 2.91 to 3.03, corresponding to an increase by 4.1%. Additionally, the average grades for essay courses are also higher than for other courses, with an average of 3.45 in the pre-treatment period. During online education, the essay grades increased by 7.0% to 3.69. The average grade for undergraduate students was 2.16 initially, but declined to 2.04 in the post-treatment period, indicating a decrease by -5.6%. For master students, the grades have increased from 3.01 to 3.19 after the treatment, suggesting an increase by 6.0%.

In Panel B, the average grade has decreased for all students from 3.21 to 3.03 when shifting from on-campus to online education, equal to a decline of -5.6%. Moreover, female students have encountered a -6.3% decrease from 3.18 to 2.98. The corresponding value for male students is a reduction of -5.3% from 3.23 to 3.06. Furthermore, the math grades have slightly increased from 3.74 to 3.79, indicating an increase of 1.3%. This increase is also true for essay courses, where the course grades have increased from an average of 3.48 to 3.73. This change is equal to a 7.2% increase. The undergraduate students have faced a decrease with -6.1%, while the master students' grade has increased by 0.3%.

Table 5 demonstrates the descriptive statistics for the passing grades at the Department of Business Administration, the Department of Economic History, the Department of Statistics, and the Department of Business Law. Since Panel C only includes passing grades, it is comparable to Panel B in 4. In Table 5, we can see that all other departments except the Department of Business Law have had an increase in the average grade during online education. Firstly, the Department of Business Administration grades has increased by 6.9% on average, where female students represent a 7.0% increase and male students a 6.3% increase.

Table 4: Descriptive Statistics of Student Grades in the Department of Economics

PANEL A	PRE				POST				
	Mean	Median	SD	N	Mean	Median	SD	N	%
All students	2.33	2	1.80	24 942	2.20	2	1.72	13 979	-5.6%
Female students	2.30	2	1.78	9 938	2.17	2	1.70	5 705	-5.7%
Male students	2.35	3	1.81	15 004	2.23	2	1.74	8 274	-5.1%
Math	2.91	3	1.87	2 416	3.03	4	1.89	1096	4.1%
Essay	3.45	3	0.97	817	3.69	4	0.98	525	7.0 %
Undergraduate	2.16	2	1.78	19 955	2.04	2	1.69	11 968	-5.6%
Master	3.01	3	1.71	4 987	3.19	3	1.57	2 011	6.0%

PANEL B	PRE				POST				
	Mean	Median	SD	N	Mean	Median	SD	N	%
All students	3.21	3	1.28	18 082	3.03	3	1.26	10 168	-5.6%
Female students	3.18	3	1.26	7 180	2.98	3	1.25	4 142	-6.3%
Male students	3.23	3	1.29	10 902	3.06	3	1.27	6 026	-5.3%
Math	3.74	4	1.18	1 880	3.79	4	1.26	879	1.3%
Essay	3.48	3	0.92	811	3.73	4	0.91	519	7.2 %
Undergraduate	3.10	3	1.28	13 900	2.91	3	1.25	8 389	-6.1%
Master	3.59	4	1.19	4 182	3.60	4	1.14	1 779	0.3%

Note: Panel A consist of failing and passing grades, and Panel B only include passing grades. PRE represent the pre-treatment period (16 January 2017 - 17 March 2020), while POST demonstrate the post-treatment period (18 March 2020 - 29 August 2021). % is the average change in grades between the two periods. Observations are on individual-level.

Furthermore, in the Department of Economic History, the average grade has increased by 8.0%. For the female students, the increase has been 7.0%, and for male students, it has been 8.3%. At the Department of Statistics, there has been an increase in grades by 5.4%. For female students, there has been an increase of 1.1%, while the grades for male students have increased by 8.6%. Lastly, the decrease in average grades for all students in the Business Law department counts to approximately -6.5%. The main negative effect comes from the female students in the Business Law department, experiencing a decrease of approximately -10.0%, compared to male students with a decrease of -3.0%.

Table 5: Descriptive Statistics of Student Grades at LUSEM

PANEL C		PRE				POST				
		Mean	Median	SD	N	Mean	Median	SD	N	%
Business Administration	All students	3.21	3	1.24	10 760	3.43	3	1.21	6 498	6.9%
	Female students	3.30	3	1.23	4 613	3.53	4	1.21	2 763	7.0%
	Male students	3.15	3	1.24	6 417	3.35	3	1.21	3 735	6.3%
Economic History	All students	3.48	4	1.16	546	3.76	4	0.91	280	8.0%
	Female students	3.71	4	1.05	174	3.97	4	0.90	95	7.0%
	Male students	3.37	3	1.19	372	3.65	4	0.90	185	8.3%
Statistics	All students	3.36	3	1.34	3 465	3.54	4	1.37	1 969	5.4%
	Female students	3.49	4	1.33	1 421	3.53	4	1.39	723	1.1%
	Male students	3.26	3	1.35	2 044	3.54	4	1.36	1 246	8.6%
Business Law	All students	2.79	3	1.16	1 705	2.61	3	1.13	1 246	-6.5%
	Female students	2.98	3	1.19	743	2.68	3	1.10	596	-10.0%
	Male students	2.64	3	1.11	962	2.56	2	1.15	668	-3.0%

Note: Panel C shows passing grades at the four other departments. PRE represent the pre-treatment period (16 January 2017 - 17 March 2020), while POST demonstrate the post-treatment period (18 March 2020 - 29 August 2021). % is the average change in grades between the two periods. Observations are on individual-level.

6.2 Wilcoxon Rank-Sum Test

The results from the Wilcoxon rank-sum test are demonstrated in Table 6, where the distribution of grades between the pre-treatment and post-treatment periods are compared. Firstly, Panel A contains all grades from A to U at the Department of Economics; Panel B excludes failing grades and thus only stretches from A to E but still only at the Department of Economics. Furthermore, Panel C shows all passing grades in undergraduate courses in all departments except the Department of Economics, while Panel D includes the undergraduate courses at the Department of Economics.

Panel A shows that all groups have a significant p-value, indicating that we can reject the null hypothesis of the distribution being equal across the groups. Accordingly, we can say that the distribution for student grades has significantly changed between the periods and thus between teaching modes. Similarly, Panel B demonstrates mostly significant results, despite insignificant math- and master's course changes.

In Panel C, economics courses are omitted and thus only contain undergraduate courses from the other four departments. The distribution of grades are significantly different comparing on-campus and online education. Lastly, Panel D also includes the undergraduate courses at the Department of Economics. Conversely, Panel D has no significant value compared to the other panels, suggesting that the change in the distribution of grades is insignificant.

Table 6: Wilcoxon Rank-Sum Test

	PANEL A		*PANEL B*		*PANEL C*		*PANEL D*	
	z	p	z	p	z	p	z	p
All students	6.768	0.000	11.641	0.000	-9.368	0.000	0.464	0.643
Female students	5.034	0.000	8.503	0.000	-8.684	0.000	-0.898	0.370
Male students	4.492	0.000	7.940	0.000	-4.394	0.000	1.801	0.072
Math	-2.354	0.019	-1.927	0.054				
Essay	-4.729	0.000	-4.938	0.000				
Undergraduate	5.611	0.000	10.779	0.000				
Master	-3.047	0.002	0.049	0.961				

Note: Comparison of distribution between the pre-treatment period (16 January 2017 - 17 March 2020), and post-treatment period (18th March 2020 - 29th August 2021) on student individual-level. In Panel C, the Department of Economics is omitted, while all five departments are included in Panel D on undergraduate level.

6.3 Ordinary Least Squares (OLS)

6.3.1 The General Impact of Online Education on Grades

In Table 7, the general impact of online education on student grades is demonstrated. Specifications (1) to (5) only includes courses from the Department of Economics, while specification (6) and (7) extends the analysis to the remaining departments of LUSEM. The variable $POST$ is positive and significant in the specifications (2) to (4), with an average of 0.168. This suggests that the grades have increased during online education by 0.168 units compared to on-campus education.

In specifications (2) to (4), the variable $TERM$ is included to estimate whether there is a time trend in student grades that varies over time. However, the small and significantly negative coefficient of 0.0599 indicates that there is a moderate negative time trend. The coefficient $GENDER$ is positive, indicating that female students, relative to male students, benefit slightly more from online education in the form of higher grades. However, the coefficient is not statistically significant in any of the specifications.

Specification (3) includes the variables $MATH$ and $ESSAY$. As shown by the significant coefficients for both variables, online education is associated with significant increases of 0.289 and 2.066 compared to non-math and non-essay courses. For $MATH$, this suggests that during online education, grades for math courses with 0.289 units higher than other courses at LUSEM. Likewise, the positive coefficient in $ESSAY$ indicates that essay courses tend to have 2.066 units higher grades compared to other courses at LUSEM during online education. These positive impacts for math and essay courses hold for all specifications (3) to (5).

Moving on to specification (4), we introduce a dummy for the level of education, $MASTER$, showing that students at the master's level have significantly higher grades of 1.115 units during online education than undergraduate students. After that, we include additional time-specific variables, a dummy for the examination date occurring in the fall semester, $FALL$, or at the re-examination period in August, $SUMMER$. The dummy variable $FALL$ indicates an insignificant increase of 0.0921 units. However, $SUMMER$ is significant, suggesting that examinations written in August tend to have 0.244 units lower grades than exams not written in the summer during the period of online education.

Moreover, in specifications (6) and (7), we extend the sample to all departments at LUSEM. Contrary to specifications (1) to (5), failing grades, math, and essay courses are now omitted. Furthermore, all courses are at the undergraduate level. As shown in specifications (6), the variable $POST$ is insignificant at -0.121 and insignificant in (7), with a coefficient of 0.0494.

Furthermore, looking at the department's dummies, all four are significant and are all positive, except for the Business Law. Firstly, the BUS variable shows that the Department of Business Administration has experienced increased grades by 1.065 units between the spring of 2019 and 2020, and a significant increase by 0.445 when looking at the entire time period. Furthermore, $STAT$ shows that the grades at the Statistics Department have increased by 1.960 and 1.661 units compared to the grades at the Department of Economics during online education. Regarding the grades at the Department of Economic History, HIS is associated with significant increases of 1.545 and 1.171 units relative to the grades at the Department of Economics. Moreover, the grades at the Department of Business Law, LAW, are not significant.

In Table 7 the R-squared spans from 0.325 to 0.438, suggesting that approximately a third of the variation can be explained by the independent variables in the model. Although this is a moderate level, we would expect an even higher R-squared if having access to factors such as course instructor or individual-level data on mental health or time spent studying for the exam.

Table 7: Impact of Online Education on Grades (OLS)

GRADE	(1)	(2)	(3)	(4)	(5)	(6)	(7)
POST	0.0503	0.167*	0.168*	0.168*	0.119	-0.121	0.0494
	(0.0718)	(0.0811)	(0.0813)	(0.0813)	(0.0844)	(0.124)	(0.0665)
TERM		-0.0599*	-0.0599*	-0.0599*	-0.0261	0.116	-0.00581
		(0.0249)	(0.0250)	(0.0250)	(0.0412)	(0.139)	(0.0305)
GENDER		0.00133	0.00282	0.00282	0.000517	0.0723	0.0546
		(0.0459)	(0.0460)	(0.0460)	(0.0458)	(0.0677)	(0.0394)
MATH			0.289***	0.289***	0.283***		
			(0.00274)	(0.00274)	(0.00286)		
ESSAY			2.066***	0.951***	1.035***		
			(0.00694)	(0.0484)	(0.0597)		
MASTER				1.115***	1.057***		
				(0.0426)	(0.0476)		
FALL					0.0921		0.0961
					(0.125)		(0.0764)
SUMMER					-0.244**		-0.184*
					(0.0726)		(0.0716)
BUS						1.065***	0.445***
						(0.0553)	(0.0210)
STAT						1.960***	1.661***
						(0.0721)	(0.0493)
HIS						1.545***	1.171***
						(0.0584)	(0.0238)
LAW						0.108	0.0223
						(0.0721)	(0.0209)
Course FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1987	1987	1987	1987	1987	600	2111
R^2	0.325	0.330	0.331	0.331	0.337	0.435	0.373

Note: Specifications (1) to (5) demonstrate all courses at the Department of Economics for both pre-treatment (16 January 2017-17 March 2020) and post-treatment period (18 March 2020 - 29 August 2021). Specifications (6) to (7) shows passing grade at undergraduate level at all departments. Specification (6) is for the spring term 2019 and 2020, while specification (7) covers the entire pre-treatment and post-treatment period. Observations correspond to the number of examinations. Clustered standard errors on course level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

6.3.2 The Impact of Online Examination on Grades

In Table 8, the results of the effect of online examinations on student grades are shown. These regressions are restricted to estimate the impact of switching to online examinations (i.e., examinations just after the 17th of March 2020) on student grades at the Department of Economics. In specifications (1) and (2), the variable *POST* is insignificant. Nevertheless, $POST$ is positive and significant in the remaining specifications, suggesting a positive impact of having an online examination on student grades. The size of the significant coefficients varies from a low of 0.403 to 0.430, suggesting an average increase of around 0.409 units. Furthermore, the variable $TERM$ suggests a significant negative impact of around -0.194 units, indicating a declining trend in grades over time.

Furthermore, the dummy coefficient $GENDER$ is insignificant and small in all specifications. The significant coefficient $MATH$ implies a positive impact on mathematical courses compared to other courses at the Department of Economics during online education of around 0.106 units. Additionally, the coefficient $MASTER$ is significant and varies from 0.347 to 0.216, suggesting that online examination is more positive for master's students compared to students at the undergraduate level. Regarding the dummy variable $SUMMER$, the coefficient is negative and significant at -0.401 in the specification (7), suggesting that examinations in the summer generated 0.401 units lower grades than examinations held during the spring.

Furthermore, in Table 8, the size of the R-squared is smaller compared to in Table 7. In Table 8, the R-squared values suggest that slightly more than one-fourth of the variation in the outcome variable can be explained by the explanatory variables. Similar to Table 7, more informative data could enhance the R-squared levels.

Table 8: Impact of Online Examination on Grades (OLS)

GRADE	(1)	(2)	(3)	(4)	(5)	(6)	(7)
POST	0.0516	0.0369	0.403***	0.403***	0.405***	0.405***	0.430***
	(0.216)	(0.165)	(0.0886)	(0.0880)	(0.0878)	(0.0878)	(0.0810)
TERM			-0.191*	-0.192*	-0.192*	-0.192*	-0.205*
			(0.0800)	(0.0795)	(0.0799)	(0.0799)	(0.0845)
GENDER				-0.0294	-0.0280	-0.0280	-0.0288
				(0.102)	(0.103)	(0.103)	(0.103)
MATH					0.106***	0.106***	0.0866***
					(0.00554)	(0.00554)	(0.00793)
MASTER						0.347***	0.216***
						(0.0216)	(0.0433)
SUMMER							-0.401*
							(0.136)
Course FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	379	379	379	379	379	379	379
R^2	0.000	0.255	0.271	0.271	0.272	0.272	0.293

Note: Passing and failing grades of courses that had exam between 18 of March - 4 of April 2020 at the Department of Economics. The period is spring term 2017, 2018, 2019 and 2020. Observations correspond to the number of examinations. Clustered standard errors on course level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.4 Differences-in-Differences

Table 9 demonstrates DiD estimates of how the students' grades have been changed by accounting for a complete transition from on-campus education to online education. Using the course NEKKPA as a control group for the estimation, the treatment effect of online education has been calculated by comparing the outcomes for the control group with the outcomes for the treatment group NEKA12.

In Table 9, the variable $POST$ is the dummy variable taking the value 1 if the examination occurs after the changed teaching mode (i.e., after the 17th of March 2020). The coefficients for $POST$ are positive and insignificant for specifications (1) to (3), varying from 0.130 to 0.133. The dummy variable $NEKA12$ is significant in (3) to (5), varying from 0.145 to 0.159. However, the main variable of interest in Table 9 is the DID-estimator $POST \cdot NEKA12$, capturing the interaction effect between the $POST$ and the $NEKA12$ variable. The interaction variable varies from around -0.545 to -0.395, indicating that the grades have significantly decreased in NEKA12 after switching to online education. The coefficient is negative and significant for specifications (1) to (5), suggesting that there has been a negative impact of online education on grades for NEKA12.

Furthermore, when including the dummy variable $GENDER$, there seems to be no significant differential effect between male and female students. Additionally, the variable $FALL$ is insignificant. Nevertheless, the variable $SUMMER$ demonstrates that the grades during the summer are significantly smaller compared to the rest of the school year, with a significant negative coefficient of -0.230 units in (5). In Table 9, the R-squared in specifications (2) to (5) suggests that around a fourth of the variation in the outcome variable can be explained by the explanatory variables in the model.

Table 9: Impact of Online Education on Grades (DiD)

GRADE	(1)	(2)	(3)	(4)	(5)
POST	0.133	0.126	0.130	0.150*	0.151*
	(0.0589)	(0.0616)	(0.0625)	(0.0596)	(0.0611)
NEKA12	0.364	0.145*	0.150*	0.157*	0.159*
	(0.208)	(0.0551)	(0.0575)	(0.0601)	(0.0580)
POST*NEKA12	-0.395**	-0.533*	-0.539*	-0.545*	-0.526*
	(0.101)	(0.185)	(0.189)	(0.191)	(0.189)
GENDER			-0.144	-0.146	-0.145
			(0.0881)	(0.0907)	(0.0904)
FALL				0.156	0.0768
				(0.111)	(0.130)
SUMMER					-0.230*
					(0.0879)
Course FE	No	Yes	Yes	Yes	Yes
Observations	475	475	475	475	475
R^2	0.027	0.232	0.238	0.243	0.253

Note: DiD for pre-treatment (16 January 2017-17 March 2020) and post-treatment period (18 March 2020 - 29 August 2021). Observations are the number of examinations. Clustered standard errors on course level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

6.5 Regression Discontinuity Graphs

The RDD graphs demonstrate the relationship between education form and grades. The blue dots to the left of the dashed line refer to the on-campus education period, while the red dots right of the dashed line demonstrates the average grades during online education. Firstly, Figure 1 demonstrates the effect of the change in average grade outcomes for all courses in the Department of Economics, including both passed and failed grades. As shown in Figure 1, the initial effect is a slight decrease in the average grade outcomes from around 2.3 to 2.25. However, this initial decrease is relatively stable throughout 2021 and 2021 but reaches lower levels in 2021 than pre-treatment levels.

Likewise, Figure 2 demonstrates the average grades for all courses at the Department of Economics. However, this Figure has excluded the failed grades (U), thus depicting only the average grades (from A to E). This explains why the grades are higher than in Figure 1 and is around 3.1 in the pre-treatment period. Just after the treatment date, the average grades decrease moderately, and the grades experience a similar trend as in Figure 1, but around lower levels.

Figure 1: Panel A: Grades at the Department of Economics

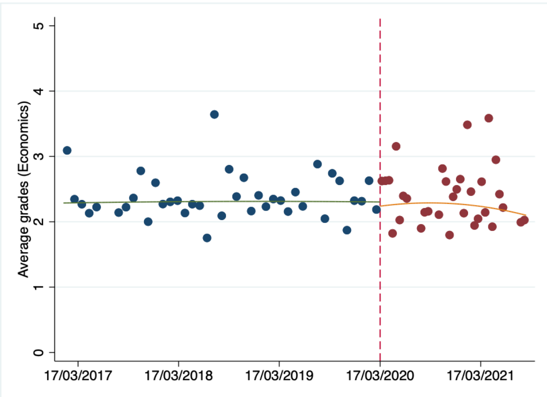
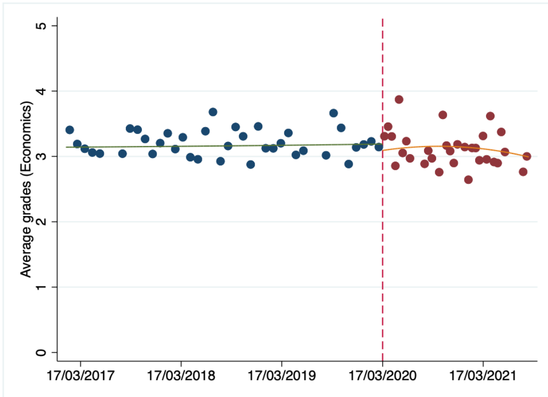


Figure 2: Panel B: Grades at the Department of Economics



Note: Both Figure 5 and 6 includes the average grades for all courses the Department of Economics. In Figure 1 both passed and failed grades are included, while in Figure 2 only passed grades are included.. The lines are quadratic, showing the best-fitted line on each side of the cut-off pint.

Furthermore, Figure 3 depicts the average grades for students taking the introductory course in economics, NEKA12. Figure 3 shows an initial upward trend in average student grades after the examination mode changed from on-campus to online in March 2020. The average grades in NEKA12 are around 1.75 just before the treatment and increase to 1.9 initially after the treatment date. However, this increase is likely driven by the examination of the financial module in the course occurring on the 18th of March.

Nevertheless, Figure 3 demonstrates that this initial upward shift flattened during the latter part of 2020 while starting to increase again in 2021. Moreover, Figure 4, demonstrates the average grades for the online introductory course in economics, showing that average grades in NEKKPA experienced a slight initial decrease after the treatment date. Though, this decrease is so tiny that the average grades do not considerably change.

Furthermore, the average grade outcomes for master's students in Economics are shown in Figure 5. The Figure shows that the average grades initially increased from approximately 3.0 to 3.1 directly after the treatment. This slight increase holds for the whole post-treatment period, and the graph demonstrates that the grades are around 3.1. The trend for the undergraduate students is demonstrated in Figure 6 and shows that the grades initially increased moderately, from around 2.5 to 2.52. Interestingly, the undergraduate grades experience a downward trend throughout 2020 and 2021. Thus, the average grades for master's and undergraduate students demonstrate different time trends in the post-treatment period.

Figure 3: Grades for Economics Introductory Course (NEKA12)

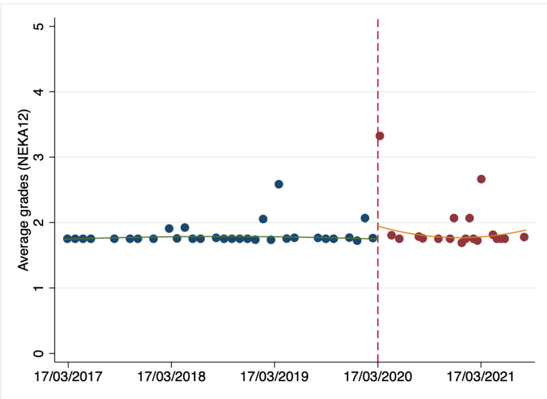
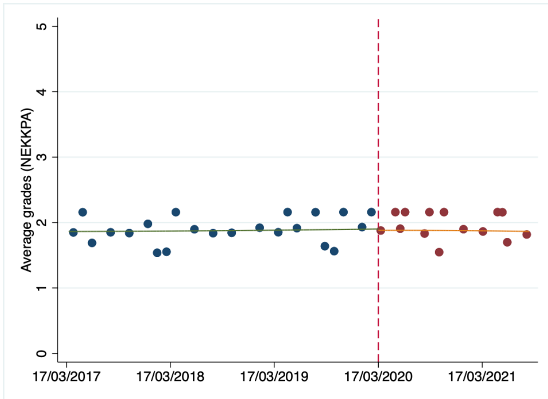


Figure 4: Grades for Online Economics Introductory Course (NEKKPA)



Note: Courses in introductory economics. Both Figure 3 and 4 includes the average grades at the Department of Economics for NEKA12 and NEKPA, respectively. Passed and failed grades are included in both figures. The lines are quadratic, showing the best-fitted line on each side of the cut-off point.

Figure 5: Grades for Economics Courses at Master's Level

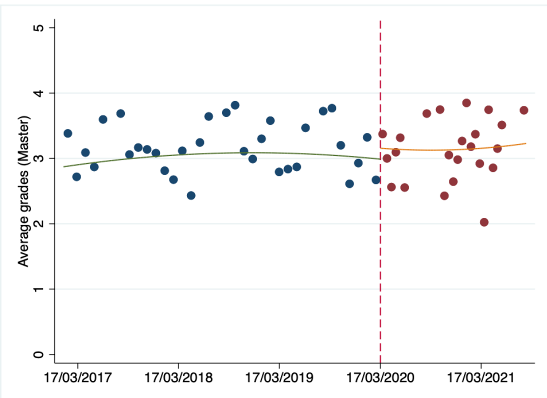
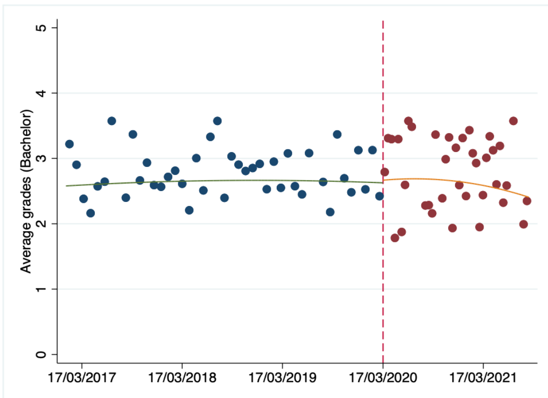


Figure 6: Grades for Economics Courses at Undergraduate Level



Note: Both Figure 5 and 6 includes the average grades at the Department of Economics for master students and undergraduate students respectively. Both passed and failed grades are included in both figures. The lines are quadratic, showing the best-fitted line on each side of the cut-off point.

6.6 Summary of Results

Table 10: Main Results by Method

Method	**Main results**
Descriptive Statistics: *Panel A*	(+) For math, essay and master courses (−) For all students, female and male students, undergraduates
Descriptive Statistics: *Panel B*	(+) For math, essay and master courses (−) For all students, female and male students, undergraduates
Descriptive Statistics: *Panel C*	(+) For all departments except Business Law.
Wilcoxon rank-sum test	Significant change of the distribution of grades for Panel A and Panel C. Insignificant change for math- and master courses in Panel B. Insignificant results for all groups in Panel D.
OLS: *Table 7*	(+) For online education in general (+) For math, essay and master courses (+) For Business Administration, Economic History and Statistics (−) For the time effect and for courses with examinations during the summer
OLS: *Table 8*	(+) For online examinations (+) For math and master courses (−) For the time effect and for courses with examinations during the summer
DiD	(−) For online education in general (−) For the time effect and for courses with examinations during the summer

Note: For the OLS- and DiD-estimations, only the significant results are included in the table. The RDD is excluded since it only includes graphical visualisation of the results. For the RDD results: see Figure 1 and Figure 6.

7 Discussion

Based on our results, there have been several interesting impacts of online education on student grades at LUSEM. Firstly, the summary statistics demonstrate that the average course grades have generally decreased at the Department of Economics. However, as Panel A in Table 4 shows, some courses have experienced positive trends, which is valid for math and essay courses as well as for courses at the master's level. The differential effect between master's students and undergraduate students might be explained by different levels of ability between the two groups (Becker 1962). Moreover, the fact that master's students, in general, spend more time studying than undergraduate students (LundaEkonomerna 2020), might make them more prepared for a new learning environment. Furthermore, master's students might also be more used to working independently, thus better equipped for an online setting.

Furthermore, as stressed by Karadag (2021), undergraduate students tend to be in larger classes than master's students. These larger courses with many students may be less flexible to adjust to a new online setting. The RDD graphs also support the positive effect for master's students during online education in Figure 5 and 6, suggesting that master courses experience an upward trend in grades during the post-treatment period, while undergraduate students experience a slight decrease.

In contrast to the findings such as Karadag (2021) and Varmaz & Veith (2021), who find an increase in grades for university students, the group all students have experienced a downward trend in grades during online education (Table 4). However, these results are somewhat in line with previous findings of Halloran et al. (2021). A possible explanation for the general decline in average grades could, for example, be that the teacher becomes less generous due to the social distance (Bohnet & Frey 1999, Hoffman et al. 1996). Alternatively, decreased grades could imply increased mental health problems among students (McCracken et al. 2020). Although the general effect points in a negative direction, there are differential impacts on other groups at LUSEM. The differential effects across groups might suggest that some mechanisms are important for some groups but less important for others.

The relatively small increase in math of 1.3% in Panel B suggests that the increased grades of 4.1% in Panel A are driven by a higher passing rate for math students during online education compared to on-campus education, which also is supported by the Figure A2. The figure also demonstrates that there has been a sharp increase in A's for math students. It might be the case that an examination in a quantitative course is unfeasible to adapt to online settings. Therefore, the examination could be more accessible or easier to cheat on math courses (Becker 1962). However, the increase in math is in contrast to the findings of Halloran et al. (2021), and Kuhfeld et al. (2020), who both finds that math grades were more negatively affected than qualitative subjects during online education.

Looking at the other departments, one interesting finding from Panel C in Table 5 is that all departments have experienced an increase in grade outcomes except the Department of Business Law. This might be due to the Business Law Department students being more used to cooperation and peer learning, and that lack of positive peer effects might drive the negative results during online education. Furthermore, the positive impact for most of the other departments stands in contrast to the general decreasing results from the Economics Department. These heterogeneous results could suggest that different policies across departments have contributed to the differential impacts of online education. If so - the Business Law and Economics Department seem to have something to learn from the other departments.

Nevertheless, it is plausible that heterogeneous effects between departments stem from other factors than only the policies adopted at the department during the COVID-19 pandemic. For example, it could be that the learning process or examinations are more challenging to adapt to an online setting in some departments compared to others. However, the negative impact across the Business Law and Economics Department suggests no evident link between the type of subject and student grades during online education since those subjects are considerably different.

Regarding the OLS estimations in Table 8, a positive effect of online examination is shown. Hence, the courses that had on-campus education but had their examination online tend to receive a higher grade than the same courses in the preceding years that had both education and examination on-campus. This impact can be contrasted to the adverse effects of online education found in the summary statistics. However, this might not be surprising since Table 8 restricts the sample to examinations held just after the recommendations for online education. Thus, this positive impact might capture the short-run effect of having the examination online, which could indicate that teachers were not able to change the structure of an exam or that higher levels of cheating occurred.

Additionally, the downward sloping time trend in Table 7 and Table 8 supports that the positive impact is short-termed. However, this increase could also be due to instructors being more generous when grading the students exposed to the rapid change in examination form compared to grading the same courses for a "normal" student cohort. This would be in line with theories on compensating behavior and social justice, such as Konow (2003), since teachers might have been more eager to "level the playing field" between student cohorts exposed to different possibilities. For example, it is feasible that teachers became more generous just after the recommendation of online education due to the uncertainty and stress of the spread of the COVID-19 virus exposed to students.

In Table 9, the results from our DiD estimations suggest that the average grades in

NEKA12 tend to have decreased more than the average grades in NEKKPA during online education. Perhaps this is not surprising due to the non-changed education mode for NEKKPA, suggesting that the grades should, in theory, remain somewhat constant. Instead, it supports the hypothesis that online education impacts student grades negatively. This negative result is in line with parts of the previous findings, such as Halloran et al. (2021), and stands in contrast to studies finding positive impacts such as Varmaz & Veith (2021) and Karadag (2021).

A possible explanation for the downturn of grades in NEKA12 could be a negative impact of peer effects when social distancing increased, and the university closed. This effect might especially apply to NEKA12 since it is introductory, which might imply that students spend much time on campus in a non-pandemic setting. Furthermore, it could be that the students who are used to on-campus education lost some motivation or felt physically unstable when forced to participate in online education from their homes. The increase in mental health problems could, for example, be because of much uncertainty about the future and the simultaneous effects of the COVID-19 pandemic.

Moreover, the RDD graphs in Figure 3 and Figure 4 masks several interesting results. For example, the course NEKA12 experience an initial increase when shifting from on-campus education to online education. Nevertheless, the upward sloping trend for the on-campus course is largely driven by the stark increase in the financial module of the introductory course. Since this particular examination occurred on the 18th of March 2020, it is plausible that the course instructor did not have time to modify the examination after the abruptly changed circumstances, resulting in an easier examination. Additionally, the fact that the examination might not have been perfect for an online setting could have resulted in more cheating, which would be in line with the theory on criminal actions as presented by Becker (1968).

The flattening curve for NEKA12 suggests that the positive impact faded over time, which implies that any mechanisms contributing to the initial increase became weaker as time passed. For example, instructors' urge to compensate students for the circumstances might have decreased at the same rate as online education improved. Alternatively, it might be the case that instructors became better at adapting their examinations for an online setting by, for example, using multiple cameras during examinations, which might have increased the probability of being caught cheating (Becker 1968, Konow 2003). Another explanation could be that students adapt to the online learning environment or the COVID-19 pandemic and subsequent restrictions.

Lastly, looking at the gender aspect, we can see that female students have a higher average grade in all departments, except in the Department of Economics, as shown in Table 5. Furthermore, female students have experienced a more significant decrease than male students when shifting to online education at the Department of Economics. Additionally, there has been a more notable negative impact for female students than male students, with a decrease of -10% and -3% in the Business Law Department. Another interesting result is that females have experienced an increase of only 1.1% in statistics, while male students have experienced an increase of 8.6%. Thus, when looking at the other departments, female students tend to have more adverse effects than male students, except in the Department of Business Administration, where the opposite holds. Summarizing these results for female and male students, male students have benefited somewhat higher than females on average. These results can be contrasted to the findings by Breaux et al. (2022), who found that male students' grades decreased, while the grades for female students did not change significantly.

8 Concluding Remarks

This study has provided thorough insights into how online education during the COVID-19 pandemic has affected student grades at LUSEM. The average grades for all students have decreased in the Economics Department, except for math, essay, and master's students. Furthermore, our OLS estimates show a significant but small increase in grades during online education. Similarly, when focusing solely on the examination form, we find an even higher positive effect of online examinations on grades in the short run. Also, the math and master courses experience significant positive impacts during online examinations, compared to non-math and undergraduate courses. Contrarily, the results from our DiD estimations show a negative impact of online education on grades for NEKA12 compared to NEKKPA, suggesting that undergraduate students are negatively affected by online education. Although our theoretical explanations highlight some possible implications, we cannot establish exactly why the results point in different directions.

By reconnecting to the main research questions in this paper, our study finds that online education has impacted student grades at LUSEM. However, the results are somewhat inconsistent and point in different directions. These results create ambiguous implications for how online education has affected student grades during the COVID-19 pandemic. Accordingly, this study cannot answer if the grades, in general, have been positive or negatively affected by online education. However, when decomposing the sample into more specific groups - we find both positive and negative impacts of online education. Thus, our answer to research question 1) is that: *yes* - there have been both positive and negative impacts of online education, and 2) *yes* - the impact varies across different courses, levels of education, subjects, and genders.

Although our study provides detailed insights into how online education has impacted student grades at LUSEM, there are some gaps in this study that further research could fill. For example, due to data limitations, we have not been able to control for all factors that might have affected grades at LUSEM simultaneously as online education has been introduced. Thus, we can be sure that online education has affected student grades, but we cannot be sure precisely what drives this effect. All mechanisms: cheating, teacher effect, peer effect, mental health and motivation, and time allocation adds critical perspectives which facilitate an understanding of the direction of our findings. However, the majority of our mechanisms are non-testable. Therefore, the exact explanation behind our results is difficult to disentangle. Further research should explore those mechanisms to extend the understanding of how and why online education impacts student grades during the COVID-19 pandemic. If one understands the limitations of online education in this setting, one can utilize this knowledge to take advantage of its possibilities. This knowledge will be useful for policy-makers and universities since it may guide them in how they efficiently can integrate online tools into higher education in the future.

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A Appendix

Table A1: Sample of Courses

		Departments of Economics - Bachelor		
NEKG11*	NEKH21	NEKH81	NEKA62	NEKA52
NEKG21*	NEKH41*	NEKH82	NEKA63*	NEKA53
NEKG41	NEKH61*	NEKG31	NEKA64	NEKA54
NEKG51	NEKH02	NEKH03	NEKH01	NEKKPA
NEKG61	NEKH71	NEKG33	NEKA12*	NEKA51*
NEKG71	NEKG81	NEKH72	NEKA61	
		Department of Economics - Master		
NEKN21*	NEKN72	NEKN86	NEKP41*	NEKN33
NEKN22	NEKN73	NEKN87	NEKP42	NEKN01
NEKN34*	NEKN74*	NEKN92	NEKP51	NEKN02
NEKN41	NEKN75*	NEKN93	NEKP32	NEKP01
NEKN51	NEKN81	NEKN94	NEKP35	
NEKN71	NEKN82	NEKN95*	NEKN31	
NEKN72	NEKN83	NEKN96	NEKN32	
		Other departments		
BUS	**HIS**	**STAT**		**LAW**
FEKA90	EKHA30	STAA30	STAG21	HARA04
FEKG61		STAA31	STAG22	HARA10
FEKG91		STAA32	STAG24	
		Math		
NEKN74*	NEKN31	NEKN33	NEKP32	NEKP35
NEKG33	NEKN32			
		Essay		
NEKH01	NEKH03	NEKN01	NEKN02	NEKP01
NEKH02				

Note: * demonstrate the courses included in Table 8.

A1 Difference-in-Difference Derivation

The DiD approach is an attempt to mimic a natural experiment by studying the differential effects on a treatment group versus the control group. Technically, in the DiD framework, we have two potential outcomes, which can be illustrated by y_{1it} and y_{0it}:

$$y_{1it} = \text{grades in course } i \text{ at time } t \text{ if education form shifts}$$

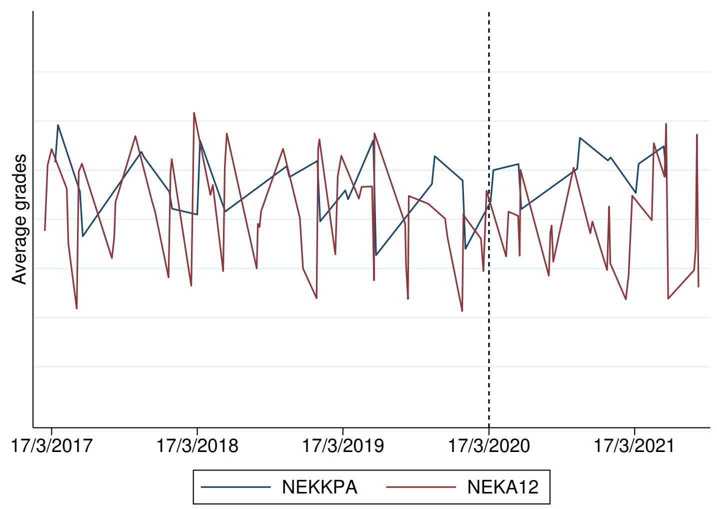
$$y_{0it} = \text{grades in course } i \text{ at time } t \text{ if education form does not shift}$$

However, in reality, we can only observe one of these potential outcomes at a time since they do not exist simultaneously. For example, after 17th March 2020, we cannot observe the grade outcome of on-campus education in course i, i.e., NEKA12. Conversely, we can only observe grades following online education in NEKA12. The idea behind the DiD framework is that in the absence of changed education form, the grade outcomes in the courses are determined by the sum of time-invariant effects in the courses added by the time-varying course effects.

Furthermore, estimating the difference between the outcomes for the treatment group and for the control group capture the causal effect of interest, illustrated by the DiD-estimator β (Angrist & Pischke 2009). In our case, the estimator β explains the causal impact of the treatment of online education on student outcomes in the course NEKA12. The above can be demonstrated by:

$$\begin{aligned} E[y_{it}|i = \text{NEKKPA}, t = \text{POST}] - E[y_{it}|i = \text{NEKKPA}, t = \text{PRE}]- \\ E[y_{it}|i = \text{NEKA12}, t = \text{POST}] - E[y_{it}|i = \text{NEKA12}, t = \text{PRE}] = \beta \end{aligned} \tag{6}$$

Figure A1: Parallel trends for NEKKPA and NEKA12



A2 Regression Discontinuity Design Derivation

Furthermore, the potential outcomes of the model can be described and estimated in a linear constant-effects manner. The potential outcomes of the RDD can be demonstrated in the following way:

$$E[Y_{0i}|x_i] = \alpha + \beta x_i$$

$$y_{1i} = y_{0i} + \rho$$

This, in turn, leads to the following regression:

$$y_i = \alpha + \beta x_i + \rho D_i + \epsilon_i \tag{7}$$

Where y_i is the outcome of average grade at examination i; ρ captures the causal effect of online education; and ϵ is the error term.

A3 Descriptive Statistics - Examination Level

Table A2: Summary Statistics of Student Grades at the Department of Economics

PANEL A	PRE				POST				
	Mean	Median	SD	N	Mean	Median	SD	N	%
All students	2.52	2.53	1.18	1 388	2.50	2.50	1.22	599	-0.8%
Female students	2.50	2.50	1.22	653	2.49	2.50	1.25	285	-0.4%
Male students	2.54	2.58	1.14	735	2.50	2.50	1.19	314	-1.6%
Math	2.57	2.83	1.23	107	2.54	2.52	1.33	47	-1.2%
Essay	3.38	3.40	0.84	257	3.56	3.71	0.83	79	5.3%
Bachelor	2.36	2.27	1.18	910	2.21	2.09	1.17	409	-6.4%
Master	2.83	3.00	1.11	478	3.11	3.12	1.11	190	9.9%

PANEL B	PRE				POST				
	Mean	Median	SD	N	Mean	Median	SD	N	%
All students	2.60	2.62	1.11	1 346	2.57	2.53	1.16	582	-1.2%
Female students	2.59	2.60	1.15	631	2.56	2.53	1.20	277	-1.2%
Male students	2.61	2.63	1.07	715	2.58	2.50	1.13	305	-1.1%
Math	2.69	2.92	1.12	102	2.71	2.71	1.19	44	0.7%
Essay	3.39	3.40	0.82	256	3.60	3.77	0.73	78	6.2%
Bachelor	2.44	2.33	1.12	880	2.31	2.24	1.10	392	-5.3%
Master	2.91	3.00	1.03	466	3.11	3.12	1.11	190	6.9%

Note: Panel A consists of failing and passing grades, and Panel B only includes passing grades. PRE represents the pre-treatment period (16 January 2017 - 17 March 2020), while POST demonstrates the post-treatment period (18 March 2020 - 29 August 2021). The column with % is the change in grades between the two periods. Observations are on an examination-level.

Table A3: Summary Statistics of Student Grades at LUSEM

PANEL C		PRE				POST				
		Mean	Median	SD	N	Mean	Median	SD	N	%
Business Administration	All students	2.94	3.00	0.75	188	3.13	3.00	0.78	91	6.4%
	Female students	2.95	3.00	0.77	88	3.20	3.21	0.85	45	8.5%
	Male students	2.92	3.00	0.74	100	3.06	2.98	0.71	46	4.8%
Economic History	All students	3.45	3.50	0.93	148	3.74	3.75	0.83	49	8.4%
	Female students	3.62	3.71	0.94	63	3.89	4.00	0.93	23	7.5%
	Male students	3.32	3.29	0.91	85	3.60	3.70	0.71	26	8.4%
Statistics	All students	3.02	3.00	0.80	167	3.06	3.00	0.88	105	1.3%
	Female students	3.08	3.00	0.82	82	2.94	2.80	0.94	50	-4.5%
	Male students	2.95	3.01	0.78	85	3.17	3.17	0.82	55	7.5%
Business Law	All students	2.31	2.29	0.71	59	2.23	2.29	0.60	32	-3.5%
	Female students	2.43	2.50	0.77	29	2.25	2.34	0.67	16	-7.4%
	Male students	2.18	2.23	0.64	30	2.20	2.19	0.53	16	0.9%

Note: Panel C shows passing grades in the four other departments. PRE represents the pre-treatment period (16 January 2017 - 17 March 2020), while POST demonstrates the post-treatment period (18 March 2020 - 29 August 2021). The column with % is the change in grades between the two periods. Observations are on an examination-level.

A4 Distribution of Grades

Figure A2: Grades for Math Courses

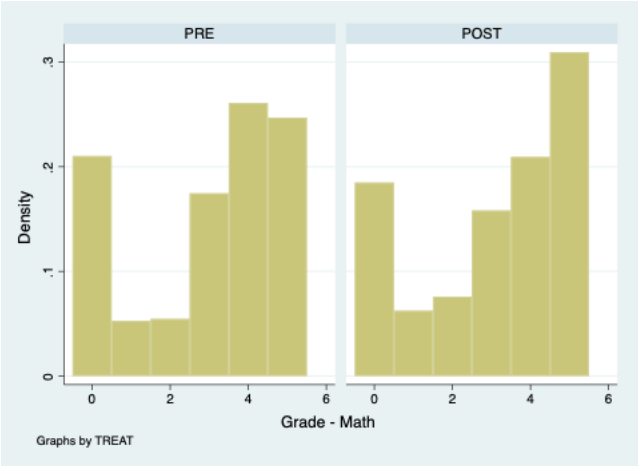


Figure A3: Grades for Undergraduate Students

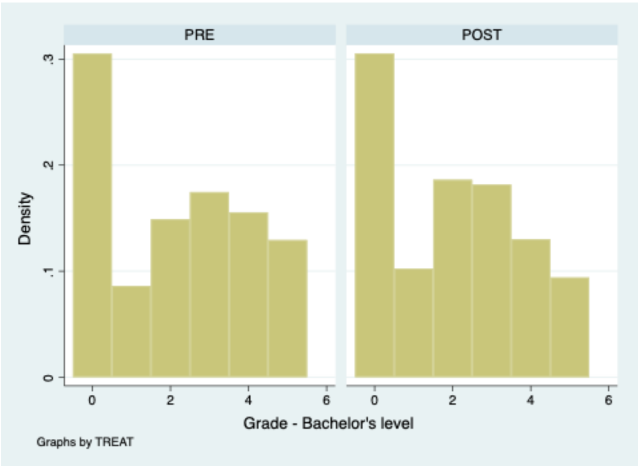


Figure A4: Grades for Master's Students