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The Effect of the Covid-19 Pandemic on Vocational College Students' Performance in High-stakes Exams*

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Abstract

A growing literature discusses negative effects of the Covid-19 pandemic on college students' learning outcomes. We extend this literature to vocational education and study the effect of the first phase of the pandemic on students' performance in high-stakes state exams across 31 Israeli vocational colleges. Two substantial advantages of this setting over previous studies are that exams were taken in person rather than on-line and that they were graded centrally and thus, were not exposed to subjective grading behavior. We estimate a difference-in-differences model, comparing early and late exams within students and across cohorts. While official grades increased due to a change in the maximum score, students' overall knowledge and exam attendance decreased. Poor internet access is the most likely driver of these negative effects compared to low socioeconomic status, more online learning, and higher infection rates.
Keywords: Higher education; Vocational Education; Education and Inequality, Covid-19
JEL classification: I23, I24

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1 Introduction

The Covid-19 pandemic and its associated lockdown and distancing policies induced major disruptions in the higher education system with profound effects on students (Aucejo et al., 2020; Faura-Martínez et al., 2022; Jaeger et al., 2021; Rodríguez-Planas, 2022b). While generally believed to have led to learning losses, it is challenging to measure the extent of such losses and to identify specific mechanisms at work, since several aspects of the educational context changed simultaneously (Altindag et al., 2021). It is particularly difficult to assess learning using exam grades due to online exams and lenient grading practices. Moreover, the existing literature on higher education is focused on college students (Rodríguez-Planas, 2022a; Altindag et al., 2021; Bulman and Fairlie, 2022; Bird et al., 2022), while the impact of the pandemic on post-secondary vocational education remains understudied.

In this paper, we use administrative data to study the effect of the first phase of the Covid-19 pandemic on students' performance in mandatory state exams in 31 vocational technical colleges across Israel. Post-secondary vocational education is an interesting setting in which to consider learning losses because the skills students are expected to acquire are practical and directly linked to the jobs that they are authorised to perform immediately after graduation.[1] Two additional unique features of our setting are that exams were conducted *in person* even during 2020, and that they were administered and graded centrally and anonymously.

The Israeli National Institute for Technical Training (NITT) designs these exams to test students' knowledge in core subjects of their study field. They are taken at different times during the two to three year study period, allowing us to compare each student's performance in "late" versus "early" exams across pre- and post-pandemic cohorts using a *difference-in-differences* (DID) framework with individual-level fixed effects. For the affected cohort, the last semester coincided with the first lockdown and the shift to online learning, with their "late" exams being taken after this semester. The standard exam procedures were maintained except for one modification which allowed students to answer more questions and gain up to 120 points rather than 100. The raw exam score is therefore not comparable to pre-pandemic scores. However, we are able to calculate the score in percentages out of the maximum to evaluate the effect on students' learning in addition to the impact on their official grades.

We find that the pandemic shock led to an increase of 22% in the likelihood to skip exams.

[1] Some study-fields also grant licensure.

When we examine the official exam grades, the likelihood to pass the exam by scoring above 55 was unchanged while the likelihood to attain a score above 80 points increased substantially, by 48% relative to the pre-pandemic mean. The lack of change in the likelihood of passing the exam could be partially explained by selection, as students who were on the margin of passing decided not to attend the exam due to the pandemic. This implies that conditional on taking the exam, the likelihood of passing actually increased. Our findings further suggest that this increase, as well as the increase in the likelihood of achieving high grades (above 80), is driven by the higher maximum exam score put in place during the pandemic. When we examine the adjusted score instead, we see that the likelihood to attain both above 55% and above 80% of the exam points substantially and significantly *decreased* relative to the pre-pandemic mean (by 12% and 49%, respectively). The practical implication is that a substantial share of graduates enters the labor force with below-threshold skills in their profession although they hold a diploma and in some cases a license.

There could be several reasons for these negative effects. Previous studies report that low SES students were more negatively affected (see e.g. Aucejo et al., 2020; Rodríguez-Planas, 2022b; Major et al., 2020). Presumably, this was due them having less access to digital technology (Bacher-Hicks et al., 2021), higher exposure to health shocks, and more acute financial stress caused by the pandemic (Rodríguez-Planas, 2022b). In addition, studies questioned the efficiency of online learning for all types of students (Altindag et al., 2021; Kofoed et al., 2021).

To further discuss potential channels of impact, we combine the administrative records with survey data on students' family and labor market characteristics and on the intensity of online teaching, as well as with locality level data on internet infrastructure quality and Covid infection rates. By estimating heterogeneous treatment effects, we show that poor internet quality was the most likely cause of the increase in dropout rate and led to a somewhat larger decrease in learning quality.

Our findings contribute to the growing body of work on the effects of the Covid-19 pandemic on educational outcomes, and more specifically to the small body of literature that focuses on post-secondary education using administrative records and quasi-experimental methods. The main findings in this literature address student outcomes during the spring 2020 semester in the US, at which time classes were moved online, exams were administered remotely which evoked concerns over cheating, and more lenient grading policies were implemented. In this setting, Rodríguez-Planas (2022a) compares within-student changes for low- versus high-income students and finds that the differential impact on their achievements depends on their previous academic achievements. Official GPAs increased for low-income low-achieving students compared to their high-income counterparts due to the use of flexible grading policies. However, looking at raw grades reveals a relative decrease in performance for low-income high-achieving students which may be attributed to problems with online learning and to financial distress. Altindag et al. (2021) focuses on online versus in person teaching in a US university utilizing variation in the extent of pre-pandemic online teaching. Using data on mid-term evaluation and final exams grades, they estimate a student and instructor fixed effects model and find an overall increase in grades, with a larger increase for students who started the semester with in person teaching. The overall improvement is attributed to more lenient grading by instructors and to changes in grading policy. Contrary to these findings, Bird et al. (2022) report an increase in student dropout and post-pandemic failing rates when compared to students with the same courses and instructors in earlier terms.

We add to this literature by offering well-identified causal evidence of the average effects of Covid on key educational outcomes of vocational college students in a nation-wide program. Our setup and data possess several unique advantages, that allow for a more general interpretation of the findings and avoid confounders related to online exams. First, the outcomes that we study are of high stakes exams that measure the skills that students acquired during their vocational training. Second, these exams are administered by an external agency and taken in person which renders them comparable across cohorts. In particular, the content and grading of these exams is standardized and thus, does not depend on the college or on the instructor. Third, while most of the learning during the semester was remote, exams were taken in person, enabling us to better separate the effect of the pandemic from any effect of a changed exam setup, including teacher leniency and cheating when exams are online. Fourth, unique data on internet access and health conditions, as well as on variation in the intensity of online learning, allow us to shed light on potential explanations for the negative effects we find.

Furthermore, to the best of our knowledge, this is the first study that addresses the effect of Covid on the skill levels of vocational college graduates. In addition to other specific characteristics of this population, the practical nature of vocational studies is likely to render online learning particularly challenging (Asgari et al., 2021). Our findings also contribute to the active discussion on improving educational content and outcomes in vocational post-secondary education which has been identified as an important policy goal. (see e.g OECD, 2016, 2019;

Nedelkoska and Quintini, 2018; Hall, 2016; Hanushek et al., 2017; Malamud and Pop-Eleches, 2010).

2 Background and Setting

2.1 Vocational Technical Colleges in Israel

We study post-secondary technological education tracks in Israel's system of technical colleges which, in addition to specific vocational skills, provide broader knowledge, similarly to academic engineering studies. These tracks are regulated by the NITT and their costs are subsidized by the government. We focus on three of the largest study fields: electrical engineering, civil engineering, and software programming which together constitute about one third of a typical cohort of students (approximately 3,000).[2] Beyond official practical-engineering diplomas, the first two fields grant licensure that enables their holder to certify plans for construction and electricity for small residential buildings.

To graduate, students are required to complete about 2,180 academic hours of coursework, submit a final project, and pass the mandatory state exams in their field of study. Colleges offer both full-time studies that take two years to complete (morning track) and evening studies that take three years (evening track). We will therefore label cohorts by the last year of mandatory coursework and exams.

The NITT administers and grades the state exams, which take place at the end of each semester. The fall semester exams typically take place from February to early March while the spring semester exams are held between July and mid September.[3] Dependent on their study major, each student takes either three or four state exams during their studies. The exact timing of each exam is predetermined by the NITT for each major and track.

2.2 The Education System in the First Phase of the Covid-19 Pandemic

On March 11 2020, Israel imposed its first nationwide lockdown, which included strict restrictions on gatherings, and the closure of businesses and public spaces. Non-essential workers

[2]The second largest field — architecture, was excluded from our analysis because the timing of exams differs substantially from that of other fields and limits our ability to test the impact of the pandemic on exam outcomes.

[3]The academic year in Israel is based on the Jewish calendar, and the exact Gregorian dates of the semesters vary by year. The academic year typically starts in October, and the spring semester in early March.

were mandated to work from home or furloughed (Bodas et al., 2022). The lockdown ended in May 2020 but certain restrictions remained in place during the summer. On September 6, the Israeli government launched the ”traffic-light” plan in which localities were classified daily by their coronavirus infection rates into either red, orange, yellow, or green status. The plan enabled the imposition of differentiated restrictions depending on the caseload in a given locality. However, the number of corona cases continued to rise, and a second nationwide lockdown began on September 18.

In response to restrictions, kindergartens, schools, and higher-education institutions fully switched to online learning during the fist lockdown, and daycares were closed. In May, when the lockdown restrictions were lifted, in person classes in higher-education institutions (including vocational colleges) were partially and gradually resumed depending on the specific decision of each institution. Still, most classes remained online until the end of the spring semester. Schools and daycares also continued to operate under substantial restrictions throughout the entire period.

Many of the exams for the spring semester were also administered on-line. However, the NITT maintained their usual exam protocol including in person exams, anonymised, centralised grading, and an unchanged threshold for passing the exam. The only change was that students were allowed to answer more questions and earn up to 120 points (instead of the usual 100).[4] Their *grade* would then be the number of points earned for correct answers capped at 100 points.[5] We note that the NITT exams always offered students some choice among questions, and that following the change, questions were added to the exam to enable a similar degree of choice.

In our analysis we account for this change by estimating the effect of the Covid shock both on the official grade and on the percent of points scored out of the maximum score which will be referred to as the adjusted grade and interpreted as the actual level of student learning. This is a reasonable interpretation if we believe that most students try to earn the highest grade that they can and do not target specific grades (which would mean that they answer fewer questions than they know the answer to). In addition, it is highly unlikely that these adjusted grades are affected by time constraints which are not considered to be tight for these exams.

[4]The score of a typical question in these exams is 20 points, and each question includes several sections.

[5]For example, if a student answered correctly questions that sum up to 90 out of the maximum of 120 points their grade would be 90 (rather than 90/120).

3 Data and Sample

The administrative database that we analyze covers the universe of students in three study fields for five consecutive cohorts ranging from 2016-2020.[6] The 2020 cohort was affected by the Covid-19 shock during their last semester of studies, while the four preceding cohorts completed their required coursework before the shock hit. These data include students' gender, age, and locality of residence, as well as their studies track, and the timing and grade for each of the state exams.

Based on the information on students' locality of residence, we supplement these data with three additional indices. First, we add a socioeconomic Z-score which is calculated by the Israeli Central Bureau of Statistics according to the population characteristics of each locality, including schooling, family size, labor force participation, and income.

Second, we construct a locality-level indicator for poor internet infrastructure based on the spread of services by the second largest internet provider in Israel (Hot Telecommunication Systems Ltd). In this duopolistic market, the largest provider (Bezeq) serves all Israeli households as obliged by law. However, according to a report prepared for the Israeli parliament in 2020, its services are of lesser quality in localities where there is no competition against the second provider.[7] Clearly, these locations are not selected randomly, but rather according to factors that determine the firm's profitability, including geographic distances from other localities, population size, and population density within the locality.

Third, we construct a locality-level measure of Covid-19 infection rates based on the "traffic-light score", where a red score defines the highest caseload. This is available for most localities in our sample (except for very small ones) for each day between September and December 2020. We calculate the share of red days in each locality during this period and use it as a proxy of the locality's infection rate during 2020, assuming that the relative ranking of localities persists over time.

In addition, we administered two online surveys in 2020 in collaboration with the NITT. The first was in June (towards the end of the semester) and addressed the heads of the 67 departments that we study, 37 of which responded (55%). In this survey we asked about the

[6]We exclude from the analysis less than 5% of these students because they study slightly different curricula or begin their studies during the spring semester.

[7]For more details see the Knesset research center report: Internet infrastructure and speed in peripheral localities - a review (November 1st, 2020; in Hebrew) https://main.knesset.gov.il/Activity/Info/Research/Pages/incident.aspx?rid=6869&businessType=1

extent of *current* online learning in the department and about any difficulties that they identify with online learning and with the Covid events more generally.

The second survey was conducted during September after the exams period. Students from the 2020 cohort were contacted through personalized SMS messages and answered the survey via their phones. The response rate after two reminders was 36%. The survey included questions about demographic characteristics, living arrangements, employment experience before and during the pandemic, and about their contact with peers and academic supervisors.

Table 1 presents summary statistics for the students in our sample based on the administrative data (Panel A) and for the subsample of students who answered our survey in the 2020 cohort (Panel B). The majority (93.2%) of students in our sample are male, they are on average older than a typical university student, and come from relatively low socioeconomic backgrounds, as indicated by the negative average socioeconomic Z-score. Accordingly, 46% study in evening tracks designated for working students.

From the survey data we further learn that almost all the students have previous work experience, with 37.5% having worked in their study field, and that almost 87% work during their studies. Despite this high share of working students and although many have spouses (37%) and children (28.6%), 51% are living with their parents (or other older relatives). During the pandemic, 14.5% of the students were furloughed or lost their job,[8] while we see smaller changes in living arrangements. The share of students moving in with parents or relatives during the pandemic was 5.1%, while a smaller share (4.3%) moved out from their parents or relatives to a more independent setup.

4 Expected Effects of Covid-19 on Student Outcomes

In this section, we discuss how the conditions created during the early phase of the Covid-19 pandemic may have changed the typical obstacles to successful studies in general and in vocational colleges in particular.

The fundamental reason for low educational outcomes among students is the suboptimal exertion of effort (Oreopoulos et al., 2022; Clark et al., 2020). This could be due to flawed time perception and poor time management (Kahneman and Tversky, 1977; Francis-Smythe

[8]We group together both options since it was not clear at the time of the survey whether furloughed workers would return to their jobs.

and Robertson, 1999), procrastination and present bias (O'Donoghue and Rabin, 1999), or inattention and distractibility (Ericson, 2017). As students in our sample are relatively old and have other commitments and responsibilities in addition to their studies, these constraints may be amplified (Bettinger et al., 2022).

The conditions caused by the Covid-pandemic are likely to interact with these constraints and affect study outcomes in several ways. Notably, the closures of daycare centers and primary schools substantially increased the additional responsibilities for students with young children (29% of our survey sample). In addition, stress due to financial uncertainty or risk of infection could affect students' ability to exert effort by limiting their cognitive bandwidth (Shah et al., 2015). Another concern is that studying from home and online classes negatively affect both the attention and the time management of students (Kofoed et al., 2021). Department heads reported low attendance rates and less effort in class during the semester. They identified online learning as the main difficulty for their students, while also mentioning financial distress and noisy home environments.

Given the practical focus in vocational studies, moving studies online is likely to have affected the quality of teaching even more negatively than in academic education (Asgari et al., 2021). Furthermore, the efficiency of online learning strongly depends on the quality of internet infrastructures, which also influences students' connectivity in general. In our survey, students with poor internet quality were more than twice as likely to report having no recent contact with fellow students and were 36% more likely to have had no contact with academic supervisors compared to students with standard internet quality.

Several of these effects could be more pronounced for low SES students, in addition to the higher risk of financial stress. First, SES is positively correlated with digital literacy and internet access, rendering online learning more difficult for low SES students (Bacher-Hicks et al., 2021). In our sample these students are 27 percentage points more likely to have poor internet access. Second, low SES communities are disproportionally affected in terms of Covid infection as can be seen in Appendix figure A1, which plots the share of high infection days against SES scores at the locality level. Third, the initial constraints are expected to be more binding for low-achieving students who tend to come from lower SES backgrounds on-average. Appendix figure A2 clearly shows this correlation.

Lastly, we note that the pandemic could also lead to positive effects on learning if, for example, it left more time for studying for those students who stopped working (14.5% of our survey sample), or if at least some students found online classes more efficient.

5 Empirical Strategy

To identify the effect of the pandemic on exam outcomes we compare results on exams that are scheduled before the final semester of studies ("early exams") to those scheduled after the final semester ("late exams") for students in the 2020 cohort, who were hit by the Covid shock during their last semester of studies. For these students, the early exams could not be affected by the Covid shock while the late ones were. To account for potential differences between early and late exams that are not pandemic-related, we include the "pre-pandemic" cohorts of 2016-2019 in our analysis and employ a DID approach.[9] We also include exam-subject fixed effects to control for unobserved, time-invariant characteristics of the subject, and individual level fixed effects to estimate within-student effects.

Table 2 presents the total number of mandatory exams for each major and the number of exams classified as late or early by major and track. There is some variation in the exam timing between different departments, and also students do not fully comply with the official exam schedule. Therefore, we classify an exam as "early" if more than 50% of students who took the exam for the first time took it before their last semester (early), and as "late" if less than 50% did so.[10] Appendix table A1 presents the full list of mandatory exams, the share of students who take the exam early by major and track, and their classification into early and late exams based on the reported shares. The share of students who take the exam early (conditional on taking it) ranges between 54% and 99% for exams *classified* as early, and between 1% and 32% for exams *classified* as late.

The exam outcomes that we consider include an indicator for attending the exam, and indicators for obtaining grades above two specific thresholds — 55, which is the threshold for passing, and 80, which is considered a high achievement. To account for the fact that for the state exams administered in summer 2020 students were allowed to answer more questions than usual and earn up to 120 points, even though the *grade* was still capped at 100 points, we also examine grade outcomes in terms of the percentage of points scored out of 120 ("adjusted grades"). As explained in section 2.2, these adjusted grades can reasonably proxy students'

[9] Some students in these cohorts took exams after March 2020 because they were behind schedule.

[10] As mentioned above, architecture was excluded from our sample since the number of late exams in this major is zero.

actual learning outcomes. Appendix figure A3 (a) compares the distributions of reported and adjusted grades. Mechanically, after the adjustment there is less variation in grades. In addition, since the reported grades cannot exceed 100 points, the 100 score bunches together all the scores between 100 and 120. In the adjusted grades distribution, these students are bunched in the 83.33 points grade which is the maximal adjusted grade (100 divided by 120). Since the outcomes that we analyse are defined relative to the 55 or 80 points thresholds, our inability to distinguish between different raw scores above 100 does not affect our results. We also note that because students do not fully comply with our division of early and late exams, some took the late exams before their last semester and thus did not require an adjustment. Therefore, we still observe values that exceed 83.33 in the distribution of the adjusted grades. Due to this partial compliance, we show the corresponding distributions for the early exams in Appendix figure A3 (b). Here, as expected, there are very small differences between unadjusted and adjusted grades.

Figures 1(a)-(d) compare the distribution of both types of grades in the 2020 cohort to that of previous cohorts, separating late and early exams. This raw data representation of the DID framework reassures us that the distribution of both the adjusted and unadjusted grades remained practically the same for the "untreated" early exams over pre- and post-pandemic cohorts, supporting the plausibility of the common trends assumption. At the same time, there are clear and substantial differences when we compare the outcomes of late exams. While the pandemic shifted the distribution of reported grades to the right, improving students official achievements relative to previous cohorts, the distribution of adjusted grades was shifted to the left, indicating a decrease in students' acquired knowledge.

To formally test these initial findings, we next estimate the following DID specification:

$$(1) \qquad y_{icdt} = \alpha_1 LateTest_t + \alpha_2 LateTest_t \times D2020_c + \theta_c + \omega_d + \vartheta_t + \lambda' X_i + \psi_{icdt}$$

where y_{icdt} is the outcome of exam t for student i in cohort c and department d. We first estimate this model with cohort, department and exam fixed effects, in addition to individual level controls including age, gender, and SES. In our main specification, we add individual fixed effects which are collinear with the cohort and department fixed effects and with the individual-level covariates. The coefficient of interest in this specification, α_2, indicates the average impact of the pandemic on exam outcomes *within* students.

6 Results

6.1 Main Effects

Table 3 presents the results of the estimation for both the unadjusted (Panel A) and the adjusted grades (Panel B). First, we show that fewer students attempted to take the state exams after the pandemic started. In column (2), we estimate a statistically significant decrease of 2.1 percentage points which corresponds to a 22% increase in the likelihood *not* to attend exams. This is a substantial effect, especially considering its severe implications on graduation. Columns (3)-(4) show no significant difference in the likelihood of passing the exam. Together with the extensive margin result, this implies that, conditional on attempting, students earned higher grades and were more likely to pass. Lastly, column (6) reports that the likelihood of scoring above 80 increases by 11.1 percentage points when estimated within individual. This corresponds to a 48% increase in the share of students with such high grades relative to the pre-pandemic mean.

In panel B, however, we report a negative effect on students' actual knowledge as proxied by the adjusted grades. The likelihood of attaining above 55% of the maximal score (the required bar for passing pre-pandemic) decreases by 8.89 percentage points, or 12% (column (4)). Furthermore, the probability of attaining above 80% of the maximal score decreases by 49%. These estimates reveal a substantial negative effect on the level of skills acquired by the students during spring 2020, although official grades increased substantially.

6.2 Heterogeneous Effects and Evidence on Mechanisms

To shed light on the mechanisms that underlie the average effects that we found, we turn to examine heterogeneous effects along several dimensions that relate to the factors discussed in section 4 above.

First, we divide the students into low and high SES subgroups according to the sample median SES score. As we show above that SES is correlated with other relevant traits, we further define subgroups by internet quality, by infection rates, and by previous achievements. Internet quality is defined as "poor" in the absence of a second internet provider and as standard otherwise. We use the traffic-light score data to classify localities with above median share of red days as "high" infection localities. To characterize students' achievement levels, we calculate their average in early exams, and divide them by the median average grade. Students who did not take any of the early exams are considered to have "low grades".[11]

An additional potential mechanism relates to the presence of children whose schools or day-cares were frequently closed. The likelihood to have children can be predicted by the students' age: in our survey data, 49.8% of the students above median age (25 years in the first year of studies) have children, compared to 5.5% of the younger students. We therefore divide the sample by this age cutoff.

Lastly, to gain some insight on the efficiency of online learning, we use data from the department heads survey, and consider students as having "high" exposure to online learning if their departments had more than 40% of their June classes online. As the response rate for the department-heads survey was only 55% and since we heavily rely on the assumption that the share of online learning reported in June is informative on online learning earlier in the semester, these results should be interpreted with some caution.

For each of these subgroups, Figures 2(a)-(e) present the estimated treatment effects and 95% confidence intervals based on the specification in equation 1 with the addition of individual fixed effects. For each dimension of heterogeneity, we report the P-value for the hypothesis that the difference between the two subgroups' treatment effects equals zero.

The results in Figure 2(a) demonstrate that the point estimates of the negative effect on the likelihood to take the exams are larger for low compared to high SES students, for students with poor compared to standard internet access, and for low compared to high achievers. However, the difference in the effect is only statistically significant (at the 10 percent level) for the division by internet quality. For the subgroup with low quality internet, the likelihood *not* to attend the exam decreased by 4.1 percentage points or 5% of the initial likelihood for this group, while for the group with standard internet, the decrease was only 1.5 ppt, or 1.6%. As shown in section 4, SES is highly correlated with internet access, however, the differential effect by internet quality is found even when we focus on the low SES subsample of students. Meanwhile, we see no difference in the effect by infection rates or by average age, two traits which are also correlated with SES and imply different channels of impact. In addition, we do not find any heterogeneity by the intensity of online learning. This could be attributed to the much smaller and selected sample for which this measure is available or to the fact that variation in online learning intensity

[11] The average grade is calculated conditional on taking the exam, meaning that students with some missing exams have their average calculated over fewer grades which may lead to bias. Reassuringly, our results are robust to replacing missing grades with either zero or 55, namely the lower and upper bound of a "failing" grade.

throughout the entire semester was quite low.[12] Overall, these finding suggest that limited internet access prevented students from effectively participating in online classes, leading to detachment from their studies, to the extent that some of them avoided even attempting to take the mandatory state exams. This choice effectively prevented them from graduating.

On the other hand, the impacts on the likelihood of passing exams shown in figure 2(b) do not present substantial heterogeneity. Figure 2(c) demonstrates that the likelihood of excelling and earning an official grade above 80 increases for all subgroups. The point estimate for high achievers is the largest (15.7) and significantly different from the effect for low achievers (5.5). Yet, the initial share of high grades also differs substantially across these two groups, and thus, the effect in percentages is actually much larger for the previously low achieving students (more than 100% compared to 35%). In addition, similarly to our results for exam attendance, low internet quality appears to attenuate the positive effects on students' official grades.

Turning to the effect on students' acquired knowledge in Figures 2(d) and (e), first, we report a marginally significant larger negative impact for low-achievers on the margin of passing (attaining more than 55% of the exam points) compared to high-achievers. There is also a substantial difference in the effect size in percentages between these two groups — a decrease of 21.6% for low achievers versus just 7.4% for high achievers. In line with our previous findings, a substantially larger negative effect is also observed for students with limited internet access although this difference is not significant at conventional levels (p-value 0.148). For high levels of knowledge (answering correctly more than 80% of the exam questions), we also observe significant differences along these two dimensions of heterogeneity but in the opposite direction. Namely, larger negative effects are found for the subgroups with standard quality internet and high-achievements, compared to those with low quality internet and low-achievements, respectively. However, the decrease in *percentages* relative to the pre-pandemic mean is more than twice as large for the latter groups. Other significant differences in effect sizes across subgroups by SES, infection rates, and age, can also be attributed to differences in the subgroups' pre-Covid means.[13]

The fact that no subgroup improved or even maintained their learning level suggests that

[12] As mentioned above, our intensity measure is based on the share of online learning reported for the last weeks of the semester, when pandemic restrictions had been relaxed.

[13] For example, heterogeneity by SES shows a very significant difference between the 15.9 ppt. decrease for high SES and the 7.6 ppt. decrease for low SES. However, the initial share of high SES students that scored above 80 is 30% while only 17% of low-achievers did so. Thus the effect in percentages for both groups is rather similar (-45% versus -53%).

mechanisms through which the pandemic could positively affect study outcomes are not dominant. These include having more study time following job loss or finding online learning more efficient.

7 Conclusion

This paper offers the first causal evidence on average effects of the Covid-19 shock on learning outcomes in post-secondary vocational education. There are two main reasons that students in vocational education may be more severely affected by the Covid-restrictions: the more practical nature of their studies and the different selection into such studies. Importantly, we identify the effect on student exam participation and grades from high-stakes, mandatory state exams taken in person and administered centrally.

We find a substantial increase in the likelihood to skip mandatory exams required for graduation. Using data on SES, internet availability, and infection rates by locality, as well as students' age and the intensity of online learning, we show that the extensive margin effect is driven by students with poor internet infrastructure, even when we focus on low-SES students. However, this extensive margin effect is offset by the increase in official grades post-pandemic, and passing rates are thus, unaffected. The increase in official grades is fully explained by a temporary grading policy that raised the maximum attainable exam score. When we use adjusted scores that better reflect learned skills, we find that students' knowledge level substantially and significantly decreased.

The state exams that we study are designed to reflect the degree of knowledge and skills of practical engineers when entering the labor market. Our findings suggest that during the spring semester of 2020, the official grades did not reflect actual knowledge which substantially decreased despite the apparent increase in official grades. These negative effects that we capture raise concerns for the proficiency of the cohorts that graduated during the pandemic, and for a potential persistence of this lack in basic skills. This is particularly worrying given the practical focus and high degree of responsibility in entry level jobs of these graduates.

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Table 1: Summary statistics

Variable	Mean	Std. Dev.	Mean (estimated)	SE	N
Panel A - All cohorts, Administrative data					
Age (years)	27.42	6.88			15352
Female	0.068	0.252			15352
Socioeconomic Z-score	-0.062	0.855			15295
Morning track	0.540	0.498			15352
Civil Engineering	0.608	0.488			15352
Electrical Engineering	0.279	0.448			15352
Software Programming	0.113	0.316			15352
Panel B - 2020 cohort, Survey data	Survey Sample		Population Inference		
Married	0.37	0.483	0.364	0.016	1059
Has children	0.286	0.452	0.280	0.015	1059
Has children under 6	0.25	0.433	0.244	0.014	1059
Has children under 10	0.286	0.452	0.280	0.015	1059
Lives with parents or other older relatives	0.509	0.5	0.515	0.017	1059
Moved to parents/relatives during pandemic	0.051	0.22	0.048	0.007	1059
Mother with Tertiary Education	0.28	0.449	0.256	0.014	960
Father with Tertiary Education	0.271	0.445	0.259	0.015	953
1st generation immigrant	0.276	0.447	0.310	0.016	1059
1st or 2nd gen immigrant	0.5	0.5	0.518	0.017	1059
Worked before studies	0.941	0.235	0.946	0.007	1059
Worked in study field before studies	0.375	0.484	0.415	0.017	1059
Worked during studies	0.868	0.339	0.870	0.011	1059
Lost job during pandemic	0.145	0.353	0.153	0.012	1059

Notes: Panel A reports summary statistics for our sample of students based on administrative data from the NITT. The socioeconomic score is based on the Z-score calculated by the Israeli Central Bureau of Statistics for each student's locality of residence in 2017. The locality of residence is missing for less than 0.4% of our sample. Panel B reports summary statistics from the 2020 cohort survey. The number of observations for parents' education is slightly smaller than for the other variables because we allowed for an "irrelevant or unknown" category which is coded as missing values. 2nd generation immigrant means that at least one of the parents is an immigrant. "Moved to parents/relatives during pandemic" is an indicator for students who lived alone or with a partner or roommates before the pandemic and reported moving in with parents or older relatives during the pandemic. Columns 1-2 show mean values and standard deviations for the survey sample, while col 3-4 show estimated population means, and standard errors of this estimator, using inverse probability weights to account for selection into the survey sample. Weights are generated by regressing an indicator for being in the survey sample on the student's age, gender, SES and fixed effects for $major \times college$. The population N in the 2020 cohort = 2,893.

Table 2: Number of Mandatory Exams and Their Timing by Major and Track

Major	Number of mandatory exams	Track	Number of early exams	Number of late exams
Software Programming	3	Morning	2	1
		Evening	2	1
Electrical Engineering	3	Morning	1	2
		Evening	2	1
Civil Engineering	4	Morning	2	2
		Evening	4	0

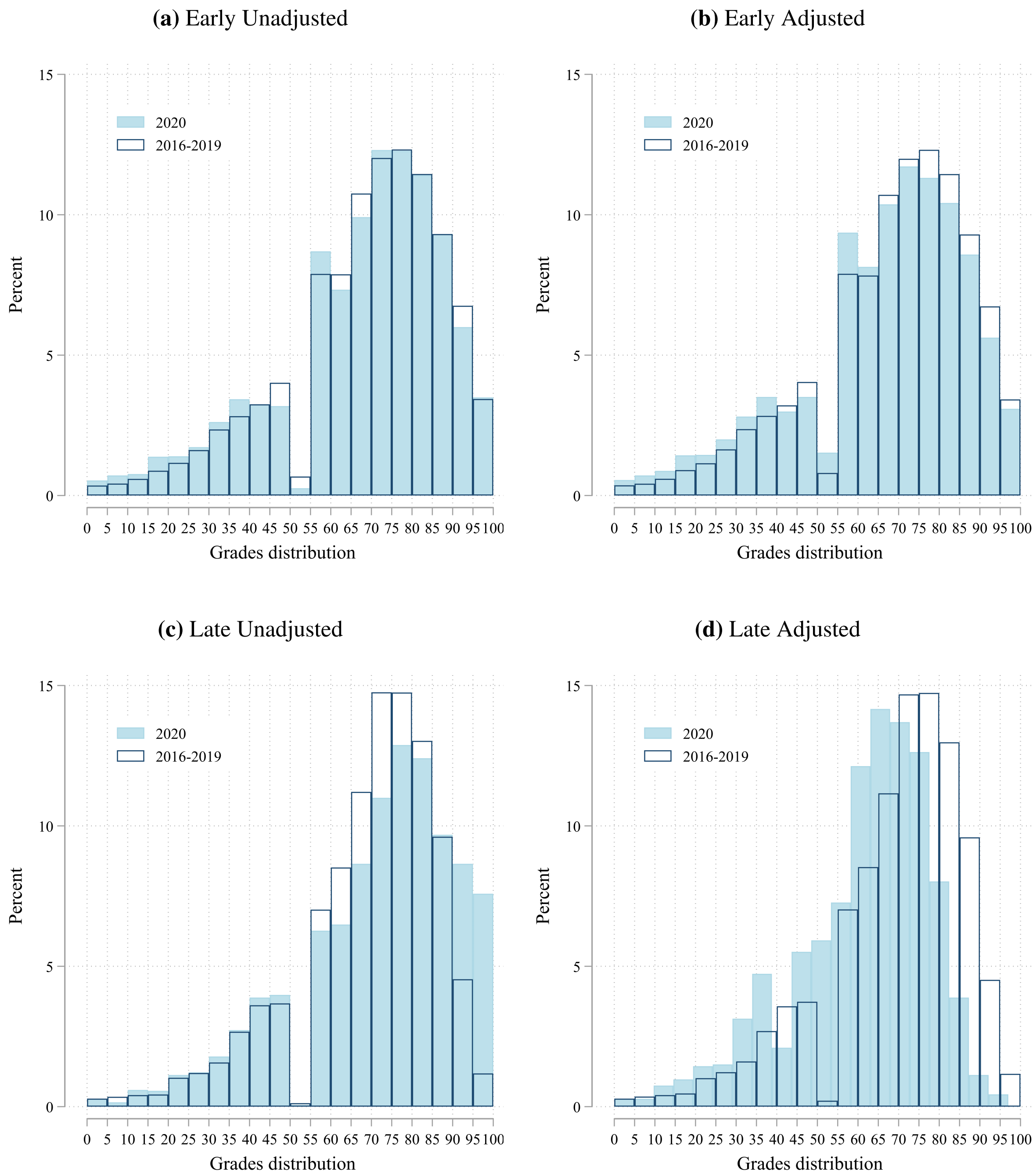
Notes: The table presents the total number of mandatory exams in each study field and their classification into late and early exam timing by track (morning or evening). An exam is defined as late (early) if less (more) than 50% of the students take the exam before their last semester, conditional on taking the exam.

Table 3: Exam Outcomes

	Attempted		Passed		Grade > 80	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Reported Grades (Unadjusted)						
Late Exam × D2020	-0.0158*	-0.0210**	-0.0153	-0.00428	0.0891***	0.111***
	(0.00923)	(0.00818)	(0.0153)	(0.0137)	(0.0176)	(0.0161)
Late Exam	-0.0221**	-0.0216**	-0.0744***	-0.0749***	-0.0478***	-0.0504***
	(0.0103)	(0.00979)	(0.0165)	(0.0156)	(0.0137)	(0.0136)
Outcome mean	0.906	0.905	0.767	0.766	0.234	0.233
Panel B - Adjusted Grades						
Late Exam× D2020			-0.0950***	-0.0888***	-0.125***	-0.113***
			(0.0158)	(0.0175)	(0.0145)	(0.0150)
Late Exam			-0.0680***	-0.0674***	-0.0376***	-0.0408***
			(0.0179)	(0.0171)	(0.0129)	(0.0124)
Outcome mean			0.765	0.764	0.233	0.232
Observations	55,179	55,395	55,179	55,395	55,179	55,395
Major×College FE	√		√		√	
Track FE	√		√		√	
Individual FE		√		√		√

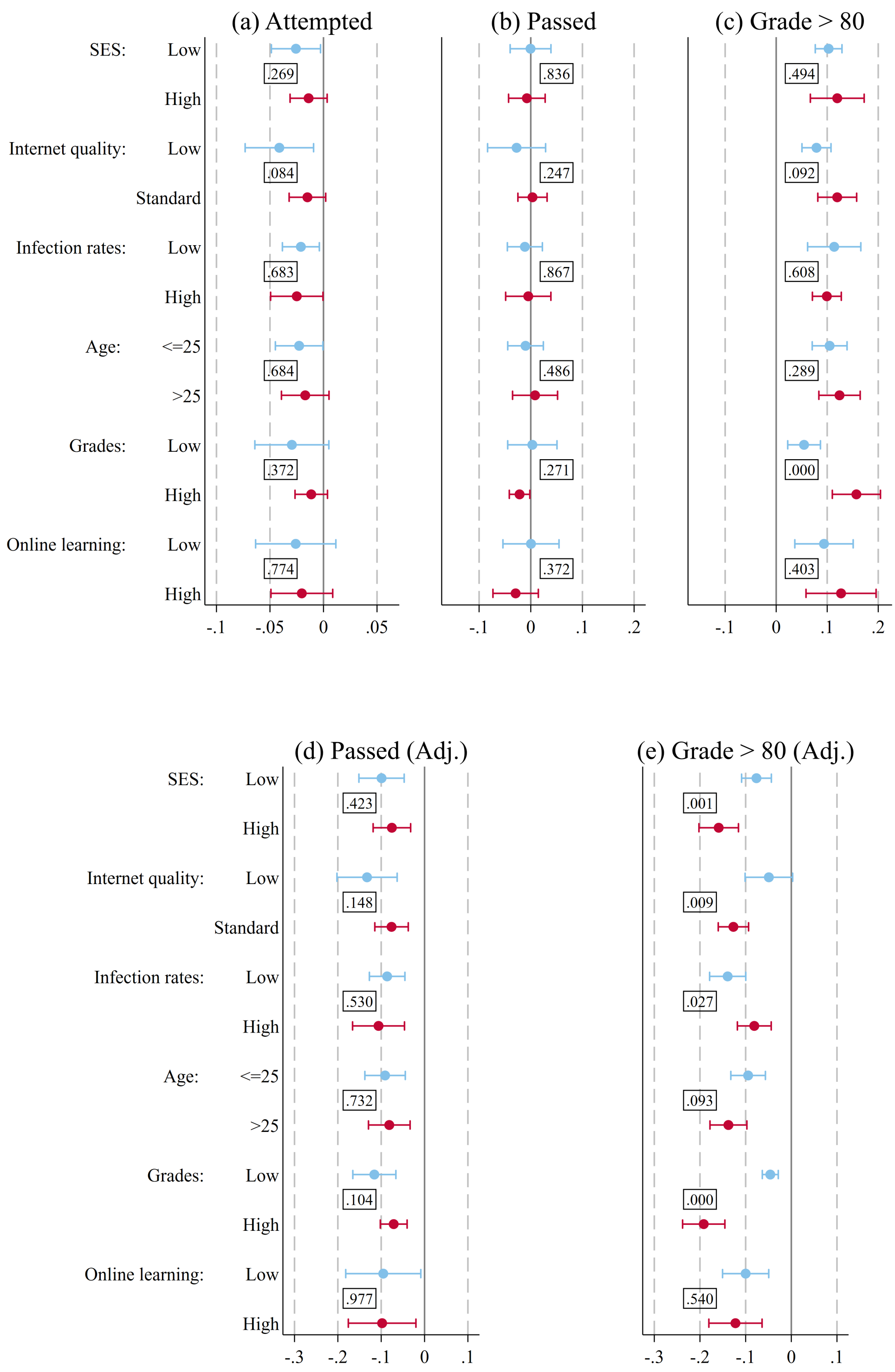
Notes: The table presents results for our main outcomes, for unadjusted grades in Panel A and adjusted grades in Panel B. “Attempted” indicates whether the student tried to take the exam at least once. This variable is unaffected by the grade adjustment in Panel B. “Passed” indicates that the student obtained a grade above 54 in Panel A or scored above 55% of the exam points in Panel B, and “Grade > 80” indicates that the student got a grade above 80 in Panel A or scored more than 80% of the exam points in Panel B. Columns 1, 3, and 5 include department and track fixed effects, while columns 2, 4, and 6 include individual fixed effects. The outcome mean is calculated using the pre-treatment cohorts and the late exams only. Standard errors are clustered by department ($Major \times College$). *** p<0.01, ** p<0.05, * p<0.1

Figure 1: The Distribution of Adjusted and Unadjusted Grades, 2020 Cohort vs. Previous Cohorts



Notes: The figures present the distribution of grades in either late or early exams, comparing their distribution for students in the 2020 cohort to that in the 2016-2019 cohorts. The unadjusted values in (a) and (c) are the reported grades, whereas the adjusted values are the reported grades divided by 120, the maximum attainable exam-score in 2020.

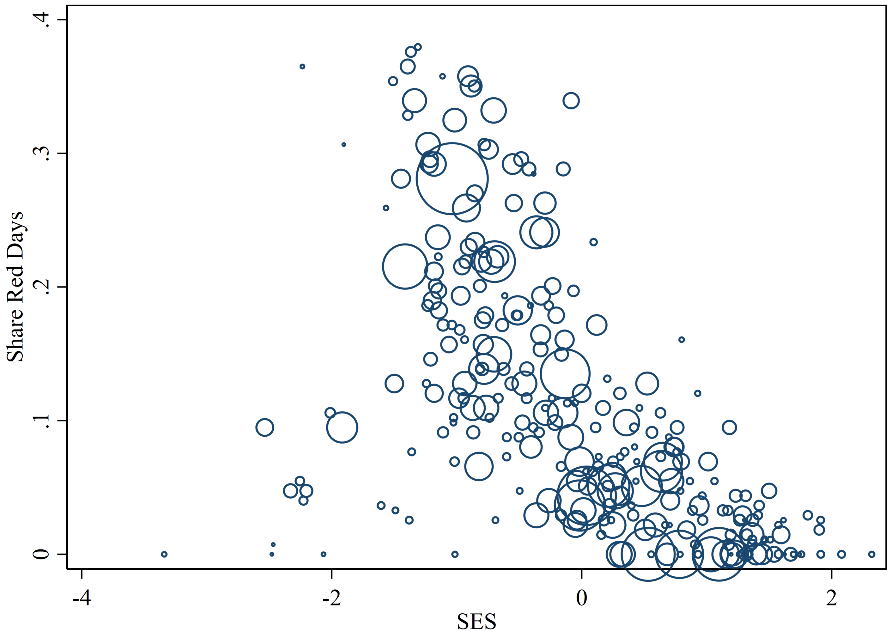
Figure 2: Heterogeneous Treatment Effects



Notes: The figure presents heterogenous effect analysis along six dimensions. P-values for the difference between the pairs of subgroups are reported in boxes inside the figures. Data on online learning is available only for a subset of 37 departments (approximately 60% of the students). Infection rates are missing for very small localities (approximately 9% of the students reside in such localities).

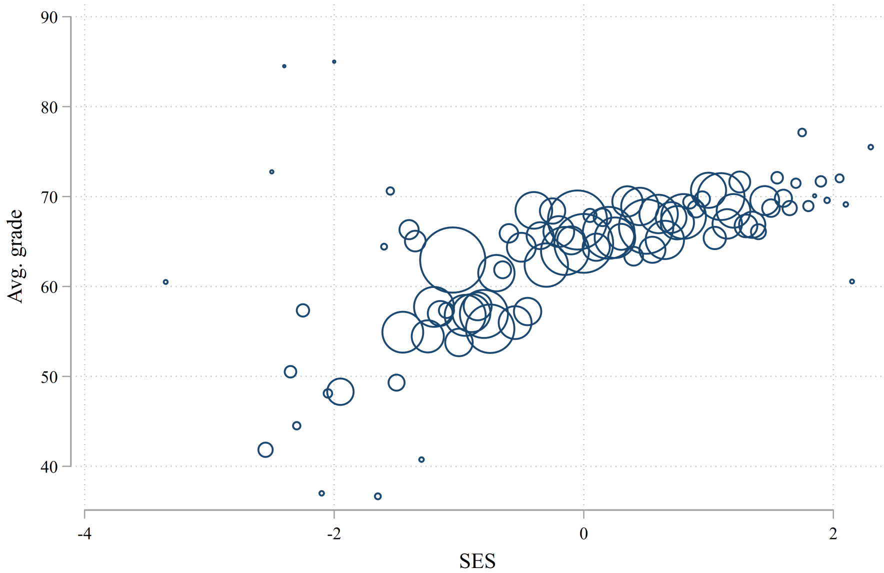
A.1 Appendix Figures and Tables

Figure A1: Socioeconomic Status and Infection Rates



Notes: The figure plots the share of "red" days according to the traffic-light score against the localities' socioeconomic Z-score provided by the Israeli Central Bureau of Statistics. A "red" score indicates high Covid-19 infection rates at the locality level. Circle sizes represent the number of students in our sample from each specific locality (number of individual-level observations).

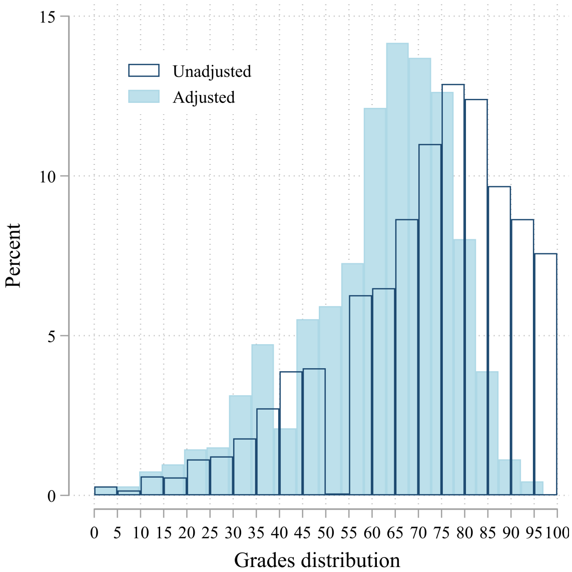
Figure A2: Socioeconomic Status and Exam Grades



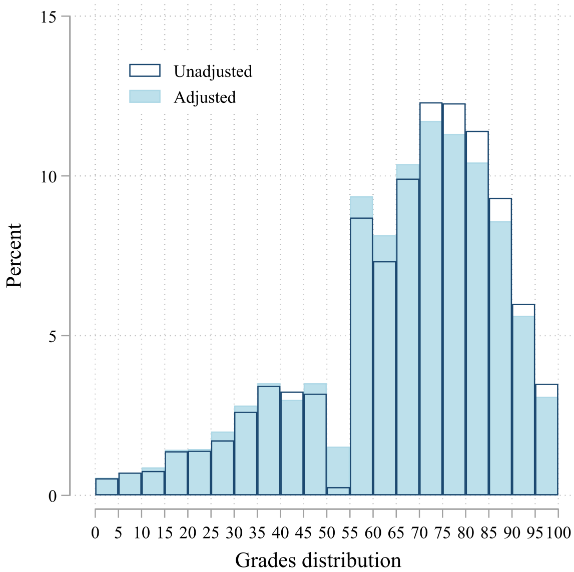
Notes: The figure plots the students' average grades in state exams taken before their last semester of studies (thus, unaffected by the pandemic even for the 2020 cohort) by their locality of residence socioeconomic Z-score provided by the Israeli Central Bureau of Statistics. These scores are binned into 0.05 intervals and the size of each circle represents the number of students in the bin.

Figure A3: The Distribution of Adjusted and Unadjusted Grades in the 2020 Cohort

(a) Late exams



(b) Early exams



Notes: The figures present the distribution of adjusted and unadjusted grades for the 2020 cohort, separately for late and early exams. The unadjusted values are the reported grades, whereas the adjusted values are the reported grades divided by 120, the maximum attainable exam-score in 2020.

Table A1: Exam Classification into Late and Early

Major	Exam id	Track	Share of students taking the exam before their final semester		Late Exam
			All students	Conditional on attending	
			(1)	(2)	(3)
Software Programming	1	Evening	96%	99%	0
		Morning	88%	96%	0
	2	Evening	14%	14%	1
		Morning	1%	1%	1
	3	Evening	85%	94%	0
		Morning	59%	70%	0
Electrical Engineering	4	Evening	86%	98%	0
		Morning	85%	95%	0
	5	Evening	86%	91%	0
		Morning	9%	9%	1
	6	Evening	25%	27%	1
		Morning	3%	4%	1
Civil Engineering	7	Evening	92%	97%	0
		Morning	11%	13%	1
	8	Evening	80%	88%	0
		Morning	49%	55%	0
	9	Evening	49%	54%	0
		Morning	28%	32%	1
	10	Evening	92%	97%	0
		Morning	89%	95%	0

Notes: The table reports the share of students that took the exam before their final semester for each exam subject by study field. Column (1) presents these shares out of all students in the track, whereas column (2) shows these shares only for students who actually took the exam. Column (3) shows how the exam was categorized for the purpose of our analysis.

A.2 Additional details on survey data

A.2.1 Details on survey data collection

We administered a survey to the 2,893 students in the 2020 cohort in September 2020 just after completion of final exams. The survey was collected electronically. A link to the survey was sent via SMS, where the sender's name was NITT (MAHAT in Hebrew). To increase response rates, the messages were personalized, and addressed students by their first name. The message further asked them to answer a short survey in order to help the NITT improve their study programs. To encourage survey response and completion rates, it also announced that survey respondents could participate in a lottery with the chance to win attractive prizes. The lottery announcement was translated to Arabic in order to increase Arab students' attention and response rates. Once opening the link to the survey, students could choose their preferred language for the survey, either Arabic or Hebrew. To make the tone more personal, the survey addressed each student according to their gender (as registered in the administrative data from NITT). This can matter, since both Arabic and Hebrew use different pronouns for males and females also in their plural forms. Therefore, many questions cannot be phrased in a gender neutral way, and we wanted to avoid the widespread practice of using the male forms to address all respondents. Wherever possible, we did however refrain from using gendered language.