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Get Rich or Fail Your Exam Tryin': Gender, Socioeconomic Status and Spillover Effects of Blended Learning

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Abstract

We evaluate a natural experiment at a Swedish university, in which students were randomized to either taking all their courses online, or to have some courses online and some on campus (blended learning). Our setting creates two groups for the online courses: One group with no access to campus whatsoever, and one group treated with campus classes in parallel, but unrelated, courses. We show that campus access in parallel courses improved academic performance in online courses only among female students with affluent parents. Detailed individual-level survey data suggests that there was no relationship between social status and adverse mental health amid the COVID-19 pandemic. Instead, by estimating each student's network position, linked with administrative data on parental income, we show that female students with wealthy parents have significantly less constrained social networks, enabling them to utilize scarcely available campus time to communicate with classmates more efficiently.

JEL classification codes: I23; I28; J16; Z13

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I. Introduction

In recent years, online coursework has gained considerable ground in higher education. This trend has been exacerbated by the COVID-19 pandemic, during which higher education facilities in most nations were temporarily closed, and in-person classes largely replaced by online teaching.

A growing body of literature examines the academic consequences of taking college courses online instead of in the traditional in-person format, with most studies finding a negative relationship between distance education and test scores (Figlio et al. 2013; Alpert et al. 2016; Bettinger et al. 2017). Blended learning, that is, mixing online and in-person teaching, also seems to have adverse effects on academic outcomes (Kozakowski 2019). Others have noted that online education increases college enrollment, particularly among mid-career individuals who would not otherwise have pursued higher education, and that colleges with higher shares of online courses charge lower tuition fees (Deming et al. 2015; Goodman et al. 2019).

In this paper, we evaluate a natural experiment among a set of second-year engineering students at Lund University, Sweden, during the Fall semester of 2020. Students were randomly assigned to either taking all of their mandatory courses online, or to have some courses fully online and some fully on campus. This produces two student groups for the mandatory courses taken online: one group having no access to campus teaching whatsoever, and one group having some, albeit unrelated, coursework on campus. We hypothesize that on-campus meetings and informal chats with peers are likely to improve learning outcomes in online courses, even if meetings take place in conjunction with classes in other courses. This hypothesis is consistent with previous studies finding significant pedagogical benefits of peer discussion and small-group learning (Springer et al. 1999; Smith et al. 2009). Communicating with classmates is likely to be facilitated by campus access, especially peers that the student is not very close friends with. In addition, campus access is likely to improve students' mental health, which is beneficial for performance in both the campus and online courses (Eisenberg et al. 2009; Cornaglia et al. 2015). We call these the spillover effects of campus teaching, and would, thus, expect positive spillover effects in online courses for students treated with parallel campus classes.

To explore whether there were any heterogeneous effects on academic outcomes depending on students' socioeconomic status, we link data on grade outcomes with detailed administrative data on parental taxable income for each student, and use this as a proxy for socioeconomic background. We utilize a number of additional individual-level controls to further isolate the effect played by socioeconomic status. Our results show that there were spillover effects of campus education only for female students with affluent parents, with the relationship increasing linearly with income. For each SEK 100,000[1] increase in annual household income, academic performance of female students treated with in-person classes increased by around 0.05σ (standard deviations).

This finding raises an important question: Are socioeconomic distortions increasing linearly with time on campus? If this were the case, we would expect that a complete return to full campus education is associated with significant socioeconomic distortions to the benefit of female students with wealthy parents. We show that there were no socioeconomic differences in grade outcomes for the previous cohort, when all education was given on campus. This result suggests that it is the blended learning setting that causes the socioeconomic heterogeneity in grade outcomes. Combining both cohorts, and using a difference-in-difference framework, we show that there is an inverted U-shaped relationship between campus time and socioeconomic distortions, with only the blended learning setting causing heterogeneity in grade outcomes with respect to gender and parental income.

What can explain this relationship between gender, parents' income and the grade outcomes of blended learning? Several recent papers have highlighted the importance of environmental rather than biological factors in intergenerational transmission, for example with respect to children's entrepreneurial success (Lindquist et al. 2015; Bell et al. 2019; Black et al. 2020). These studies often point to network effects as one of the keys in explaining the relative importance of "nurture" in this context. In our setting, one potential network-related channel is structural embeddedness, which is defined as the degree of overlap between the social networks of two individuals (Granovetter 1985). In essence, the lower the number of mutual friends shared by two people, the more open is the social network around these two individuals. Being connected across groups improves access to novel ideas, reduces information redundancy, and promotes alternative ways of thinking (Burt 2004). Such traits are likely to have a positive impact on academic outcomes. Given previous research, it is plausible that the network status of parents[2] extends to their children (Kohn et al. 1986; Coleman 1988; Conti and Heckman 2010). An alternative explanation to our findings is that female students from wealthy backgrounds are less stressed or anxious about the pandemic, and can make more of the campus experience.

Consequently, the second set of results concerns the mechanisms behind the finding that socioeconomic status is positively correlated with campus spillovers under blended learning. Immediately following the end of the semester, we survey the same set of students. In our survey, we combine a standard questionnaire on studying habits and mental health with questions about students' social networks. We show that students treated

[1] At the time of writing, 1 USD ≈ 8.30 SEK. Hence, SEK 100,000 ≈ USD 12,000.

[2] Recent research underscores that both parents' stratification status impacts children's social networks, and by extension also the potential for intergenerational mobility, as opposed to previous theories focusing only on the role of fathers (Beller 2009; Mare 2015).

with campus classes are more motivated to study, and report lower levels of mental distress vis-à-vis students without in-person classes. These results hold even after controlling for pre-pandemic quality of life. After education for all students moved fully online towards the end of the Fall semester, there was no difference between treated and untreated students with respect to self-reported mental health, suggesting that the difference observed earlier in the semester was indeed due to campus presence. Importantly, however, we find no relationship between mental health and gender or parental stratification status, meaning that our results are unlikely to be explained by differences in anxiety about the pandemic and its consequences on social life.

Instead, we turn our attention to the role played by social networks. Using the results from our questionnaire, we graph the classmate social network among students treated with campus education, and use the estimated network positions to compute network constraint for each individual student. By linking estimated network constraint with the same administrative data on parental income, we show that students with affluent parents have more open social networks, suggesting that these students can more efficiently bridge "holes" in the social structure.[3] We additionally show that female students with wealthy parents treated with campus classes spend more of their study time physically meeting peers, compared with other student groups. Consistent with our theory, this result suggests that campus communication acts as a catalyst for students stretching across network clusters, and that female students whose parents are at the highest end of the stratification hierarchy are the most efficient network "brokers". Considering that even treated students had limited access to campus, our results are consistent with recent findings that network brokerage is particularly useful when time for socializing with peers is scarcely available (Mullainathan and Shafir 2013; Burt 2017; Opper and Burt 2021). Alternatively stated, limited access to peers in a blended learning setting raises transaction costs for social interactions, making it difficult for less connected students to interact with peers.

This paper makes a number of contributions. First, we add to the growing literature on the heterogeneous effects of the closing of educational facilities during the COVID-19 pandemic. In the United States, the adverse learning outcomes associated with the closing of K-12 schools was disproportionately skewed towards low-income students, whereas internet search frequency for online educational resources was higher in affluent areas (Chetty et al. 2020a; Bacher-Hicks et al. 2021). Another strain in the literature focuses on the heterogeneous consequences of lockdown on mental health. Two studies from the U.S., and Greece, respectively, show that self-reported anxiety among university students was higher among females than males (Kecojevic et al. 2020; Patsali et al. 2020). Similarly, students with access to a yard or garden experienced lower levels of anxiety during

[3]An absence of a direct tie between two individuals in a social network is referred to as a *structural hole*.

the lockdown in France (Husky et al. 2020). We add to this literature by showing that having some campus classes is beneficial for mental health compared to full online mode, however, distance education was not associated with an overall deterioration of academic grades.

Second, we contribute to the literature on heterogeneity in social networks depending on socioeconomic characteristics. Previous research has shown that parental socioeconomic status is associated with relatively higher shares of acquaintances in individual social networks, concomitant with a higher rate of socializing with friends, but lower rates of socializing with relatives (Andersson 2018). Among university students, those coming from privileged backgrounds are more likely to communicate and interact with faculty (Kim and Sax 2009), and higher levels of network centrality is associated with improved academic performance (Calvó-Armengol et al. 2009; De Paola et al. 2019). In terms of gender, while it has not been established that women have broader networks overall, being embedded in networks that are diverse, for instance with respect to the gender and socioeconomic status of group members, is more likely to benefit women than men (Lutter 2015; Mengel 2020). On the other hand, single female college students are less likely to portray themselves as ambitious if their choices are observed by male peers, which would be the case for many of our sampled students during in-person classes (Bursztyn et al. 2017).[4]

We add to the literature on heterogeneity in social networks in two ways: First, by showing that parental socioeconomic status is one important channel in explaining the heterogeneity in network constraint observed among students, suggesting that there is significant intergenerational transmission of network status. Second, we show that network constraint is an important mechanism behind the observed spillover effects of campus education in a blended learning setting, and that network constraint is lower among females and students with affluent parents.

Finally, we contribute to the broader literature on social networks and their role in shaping economic outcomes. Previous research has shown that individuals with higher network centrality and openness have shorter unemployment spells (Cingano and Rosolia 2012), higher savings rates (Breza and Chandrasekhar 2019), are more likely to be elected into political office (Cruz et al. 2017), and that CEOs with higher network centrality are more successful in finalizing merger and acquisition deals (El-Khatib et al. 2015). We contribute to this literature by showing that network structure is an important mechanism in explaining variations in academic outcomes when education is partially online.

The rest of the paper is structured as follows. Section II provides additional details on the experiment setting. Section III describes the data. Section IV presents the results, while Section V discusses potential mechanisms. Section VI concludes.

[4]According to a student-run poll done among students enrolled in one of our sampled programs (Industrial Engineering), 60% of respondents were single (Sandström 2020).

II. Setting

II.A. Background

We study a natural experiment conducted at the Faculty of Engineering at Lund University, Sweden, during the Fall semester of 2020. Starting March 17, 2020, higher education facilities were ”strongly recommended” by the Public Health Agency of Sweden to switch to online-based teaching in order to mitigate the spread of COVID-19. Hence, the reminder of the Spring semester was fully online at all public universities in Sweden, including Lund. The recommendation about online education lapsed on June 15, 2020, but was reinstated in early November.

Since public universities in Sweden are their own government agencies, they have significant leeway in interpreting regulations and recommendations from other government agencies. Following the summer holidays, teachers[5] at the Faculty of Engineering could decide for themselves whether to continue with online-based education, or return to campus. The only prerequisite for in-person teaching was that student groups could not be larger than 50 individuals, and that the number of seats in lecture halls were required to be twice the number of students in class, in order to ensure social distancing. However, as the number of students enrolled in most of the Faculty's undergraduate programs exceeds 50 by some margin, the former requirement meant that the bulk of courses were given online, in order for instructors to avoid the extra teaching burden associated with splitting students into two or more lecture groups.[6] Whether a course was to be held online or at campus was unknown to students until around one week before the start of the Fall semester.

Swedish universities follow the standardized system for comparing academic credits across the European Union, the so-called *European Credit Transfer System* (ECTS). One academic year is equal to 60 ECTS credits, which corresponds to 1600 hours of full-time studies. There are two semesters in an academic year (Fall and Spring), with 30 ECTS worth of coursework in each. In addition, each semester is divided into two terms; for the Fall semester, the terms are September–October, and November–December. Most courses run for one term only, which places a relatively high emphasis on final exams. However, courses running for an entire semester typically have mid-term exams, to avoid examining four months of coursework in a single day.

[5]Throughout this paper, ”teacher”, or ”instructor”, refers to the person responsible for giving lectures and planning exercise sessions, regardless of academic rank.

[6]Teaching credits provided to instructors were the same regardless of teaching mode.

II.B. The Experiment

We consider the academic results of second-year students enrolled in four separate undergraduate engineering programs: Engineering Mathematics (EM), Engineering Physics (EP), Industrial Engineering (I), and Mechanical Engineering (M).[7] During the Fall semester of 2020, students enrolled in EM and I took the same mandatory course in introductory microeconomic theory, which was given in person with students split into two lecture groups based on surnames. Hence, students in these two programs constitute the treatment group, as they had at least some campus classes during this time period. Students enrolled in EP and M had no campus classes whatsoever during the Fall semester, meaning that these students constitute the control group.

We proceed by using data on student performance in two courses taken during the same semester as the microeconomics course: a mathematics course for students enrolled in EM and EP, as well as an introductory course in supply chain management for students in I and M. Consequently, this design creates one treated and one untreated student group for each course, where the treatment is access to campus teaching in other courses.[8]

Table 1 describes the course structure used in the experiment in some additional detail. We are interested in grade outcomes for the two online courses "Complex Analysis" for EM and EP students, and "Supply Chain Management" for students enrolled in I and M. As the name suggests, the course in complex analysis deals with complex-valued (holomorphic) functions, with first-year courses in calculus and linear algebra being prerequisites, whereas the course in supply chain management builds directly on a course in operations management taken by I and M students during their first year. In the mathematics course, EM students are treated with in-person classes in their parallel microeconomics course (but not in Mathematical Statistics), whereas EP students have no access to campus whatsoever in their courses in Dyanamics and Statistical Thermodynamics. Similarly, for the course in supply chain management, students in the I program have the online mathematical statistics course and the on-campus microeconomics course in parallel, whereas M students have no campus access in their parallel courses. If it is the case that there are spillover effects from campus teaching, we would expect the treated students to perform relatively better in the online courses than their non-treated peers.

Our experiment design has numerous advantages. First, there is no selection into courses, since all courses in the first and second years are mandatory. Second, the design

[7] All are five-year degree programs leading to an M.S. in Engineering. All four are among the most competitive engineering programs in Sweden, with most of the students having scored grade A in all of their subjects in high school. Table A.1 of Online Appendix A provides the course structure for each program.

[8] Although students without in-person classes were not explicitly banned from university premises, students were advised not to visit campus unless they had scheduled classes.

is not subject to any teacher fixed effects, because the instructor for each of the two spillover courses is the same individual, regardless of student group. The mathematics spillover course has the additional advantage of both student groups writing the same final exam (late-October), meaning that the exam questions faced by students are the same regardless of treatment. The final exam for the course in supply chain management is in late-October for students in the I program, and in early January for M students, however, the course material and instructor are the same for both programs. Thus, although the decision by individual teachers whether to remain online or to switch to campus teaching is plausibly affected by unobservable teacher fixed effects, the quality of the online course will be the same regardless of whether the student group received campus treatment in their parallel course or not.

III. Data

III.A. Data Overview

At the Faculty of Engineering, passing grades are given by 3, 4, and 5, with 5 being the top grade. The grading scale is absolute, meaning that the cutoff level for each grade is determined before the start of the course, and is not affected by the relative performance of students.

In order to isolate the effect of campus access on academic outcomes, we use a set of control variables. Since we are particularly interested in the role played by socioeconomic factors, we use administrative data from the Swedish Tax Authority to calculate the taxable income of each parent for the year 2019.[9] We then calculate the average of each parent's income and use this as a proxy for the student's socioeconomic background. Overall, the parents of our sampled students are considerably wealthier than the median in Sweden, with the median parental income at SEK 567,350.[10] Figure A.1 of Online Appendix A illustrates the box-and-whisker diagrams of average parental income for students in each engineering program, measured in SEK.

We employ a number of additional student-specific controls, namely age, whether the student has non-Western background, that is, both parents born in a non-Western country, and the median income of the student's home municipality. Online Appendix B presents the data sources for all variables used in the empirical analysis, and provides additional definitions.

[9]Sweden has no joint family taxation.

[10]The median income for individuals aged 20–64 was SEK 337,400 in 2018 (*Data source*: Swedish Statistics Agency.). It is well-known that top-ranked universities tend to disproportionally enroll students from high-income families (Chetty et al. 2020b). However, since there are no tuition fees in Sweden, it is likely that this gap is smaller than for many other universities of similar standing.

III.B. Survey Construction

To examine mechanisms and to perform additional robustness checks, we survey students from the four engineering programs immediately after the end of the Fall semester, by constructing an online survey consisting of 21 questions. We emailed an online link to each of the 333 students enrolled in EM, EP, I, and M, followed by two reminder emails after 48 and 96 hours, respectively. Each respondent was awarded a gift card worth SEK 50. In total, we received 151 responses, corresponding to a response rate of 45 percent. The survey questions fall into three categories: socioeconomy, opinions about coursework in the Fall semester, and questions about mental health and social networks.

In the final question, we ask students to name up to five of their closest classmates. On average, students participating in the survey named 4.07 friends. Here, we encounter a frequent problem in social network analysis, namely tie non-response. Because ties represent social interactions between individuals, estimates of network strength are likely to be biased even with relatively low rates of non-response (Kossinets 2006; Smith and Moody 2013). To correct for non-response, we use that during the microeconomics course for EM and I, students self-selected into groups of 3–4 classmates when writing a mandatory group assignment. Of the 36 groups in total, there were 15 three-person groups and 21 four-person groups. This allows us to impute up to three alters (friends) for the non-responding students. A major advantage of this procedure is that it enables us to fully eliminate non-response among the EM and I students, as well as to link students' network positions to parental income. We can also show that the share of non-responding students was random between groups.[11] However, since we are only able to perform the imputation for EM and I, we drop this question for the remaining students.

Table A.2 of Online Appendix A presents a balance test, comparing the universe of students in our dataset with our survey sample with respect to the share of treated (I and EM) students, the share of female students, and the median income of the students' home municipalities. There are no statistically significant differences between the survey sample and the overall dataset with respect to these student characteristics.

[11] We construct a contingency table with two frequency columns (the number of group members participating in the survey, and the number of group members for which the friendship alters were imputed), and 36 rows, corresponding to the number of student groups. The test statistic for testing the null hypothesis that non-response is random between groups is $\sum_{i=1}^{r}\sum_{j=1}^{c}\frac{[O_{i,j}-E_{i,j}]^2}{E_{i,j}} \overset{\text{asy.}}{\sim} \chi^2(35)$, where for outcomes i and j, $O_{i,j}$ is the observed frequency, and $E_{i.j}$ is the expected frequency if non-response is random. The observed chi-square score is 33.10, which is equivalent to a p-value of 0.56. A concern would otherwise be that, for instance, female-only groups were more likely to have a larger share of members participating in the survey.

III.C. Operationalization of Parental Stratification Status

One of our research questions is related to whether there is variation in academic and non-academic outcomes depending on parental socioeconomic status. However, it can be difficult for students participating in the survey to precisely estimate their parents' income. To tackle this issue, we construct a socioeconomic status index based on four questions in the survey, each asking the respondent to state, respectively: (i) in which municipality he or she lived just before starting university, (ii) in what type of dwelling he or she mainly lived during childhood, (iii) whether any of their parents has a college or university degree, and whether (iv) anyone of their parents has been the CEO or a board member of a publicly listed company during the lifetime of the respondent.

For each of the above questions, we proceed by assigning a numerical value to each response.[12] Respondents from more affluent municipalities receive a higher score, where the score is proportional to the median disposable income of the municipality. Similarly, respondents who grew up in a house receive a higher score than those living in rental apartments during their childhood, as do respondents for which both parents have a college degree. Finally, respondents where at least one parent has been the CEO or a board member of a publicly listed company receive the score 4, compared to 1 for those without a CEO or board member parent. The latter variable is the one most likely to capture those with the highest-earning parents: the data presented in Table A.4 of Online Appendix A shows that out of the 20 parents with the highest reported taxable income, 16 had at least one CEO position or board assignment during the lifetime of their children, and 15 had at least one current assignment. Of the top 7 parents, all had at least one CEO or board assignment.

To construct the index, we denote questions by $j = 1, \ldots, 4$, and sum the numerical scores obtained in each question to form the *Socioeconomic status index* for student $i = 1, \ldots, 151$ as

$$\text{Socioeconomic status index}_i = \sum_{j=1}^{4} \text{Score}_{ij} \tag{1}$$

It can be shown (see Theorem B.1 of Online Appendix B) that the minimum and maximum values of (1) are 5.78 and 15.43, respectively. However, to facilitate interpretation, we standardize the index so that its sample mean is equal to zero and its sample standard deviation is equal to unity. Hence, the higher the z-score associated with the respondent's socioeconomic status index, the more affluent is the family background of the respondent.

Online Appendix C provides additional details on the structure of the questionnaire, as well as the exact wording of the questions and answers available to respondents. Online Appendix D presents the full results for each question in the survey.

[12] Table A.3 of Online Appendix A presents the contribution of each question to the total index value.

III.D. Summary Statistics

Table A.5 of Online Appendix A presents the summary statistics for the 2020 cohort. We have previously showed that the parents of our sampled students are wealthier than average. The proportion of females is around 28%, and the share of students with both parents born in a non-Western country is approximately 6%. There is less variation in age, the average age being around 21. Table A.6 of Online Appendix A gives the same summary statistics for the previous (2019) cohort, the academic outcomes of which are also utilized in the empirical analysis. There are no major differences in any of the variables of interest between the two cohorts.

IV. Spillover Effects of Campus Access on Online Coursework

In this section, we examine the grade outcomes of students depending on campus treatment in parallel courses. Additionally, we implement a difference-in-difference strategy to evaluate the grade effects in the current cohort compared to last year's, when all instruction was in-person.

IV.A. Main Results: Blended Learning versus Full Online

1. Estimates for the Current Cohort

Denote by $y_i \in \{3,4,5\}$ the grade obtained by student i in either the mathematics course (EM and EP) or supply chain management course (I and M). Both courses build heavily on first-year courses: Complex Analysis on first-year mathematics courses in calculus and linear algebra, and Supply Chain Management on the first-year course in operations management. Consequently, for EM and EP students, we let Δy_i be the difference between y_i and first-year mathematics GPA, and for I and M students, Δy_i is the difference between y_i and the grade in the first-year operations management course. Finally, we standardize Δy_i so that its mean is equal to zero and its standard deviation is equal to unity.

In this paper, we are particularly interested in the role played by parental position in the stratification hierarchy, and whether the effects were particularly strong for male or female students. Thus, we estimate

$$
\begin{aligned}
\Delta y_i = \alpha_0 &+ \beta_1 \text{Treated}_i + \beta_2 \text{Inc}_i + \beta_3 \text{Gender}_i + \beta_4 \left(\text{Treated} \times \text{Inc}\right)_i \\
&+ \beta_5 \left(\text{Treated} \times \text{Gender}\right)_i + \beta_6 \left(\text{Gender} \times \text{Inc}\right)_i + \beta_7 \left(\text{Treated} \times \text{Gender} \times \text{Inc}\right)_i \\
&+ \boldsymbol{\gamma}' \boldsymbol{X}_i + \varepsilon_i \qquad (2)
\end{aligned}
$$

where $\text{Treated}_i \in \{0, 1\}$ denotes whether the student was treated with the parallel campus course or not, Inc_i denotes the average annual income of parents, $\text{Gender}_i \in \{0, 1\}$ is zero for males and unity for females, $\boldsymbol{X}_i$ is a vector of student-specific controls (age, non-Western background of parents, and median income of home municipality), and ε_i is an error term. Hence, if there are spillover effects of campus education regardless of gender or socioeconomic background, we would expect the coefficient estimate $\hat{\beta}_1$ of β_1 to be positive.

Table 2 presents the results. In columns (1)–(3), the standard errors are clustered at the program level. When the number of clusters is low, using clustered standard errors tends to over-reject the null hypothesis $\beta_i = 0$. In our case, there are only four clusters, so we adjust the standard errors with a wild cluster bootstrap (Cameron et al. 2008) with bootstrap weights drawn from a Webb distribution, which has been shown to work well in settings when the number of clusters is below 10 (Webb 2013; Cameron and Miller 2015). The bootstrap-adjusted results are given in columns (4)–(6), with the p-values for the null hypothesis that the parameter corresponding to the coefficient estimate is equal to zero in square brackets.[13] We see that the coefficient estimate for treatment with campus access, $\hat{\beta}_1$ is negative, although statistically insignificant. When using the full model as described by equation (1), corresponding to Columns (3) and (6) in Table 2, we see that the only statistically significant coefficient is the triple interaction term $\hat{\beta}_7$ between treatment, female gender and average parental income. The triple interaction coefficient estimate is positive, suggesting that the effect is increasing with income. If average household income increases by SEK 100,000, which is approximately equal to USD 12,000 (so that the average income of each parent increases by SEK 50,000), academic performance of treated female students increases by 0.05 standard deviations.[14] The remaining coefficients are all statistically insignificant.

It can be challenging to interpret the coefficients when there are three-way interactions. To facilitate interpretation, we perform an out-of-sample forecast, varying only treatment status, gender, and average parental income, using different values for the latter in the interval between 0 and $3,500,000$.[15] Figure 1 presents the contour plot of the predicted standardized values of Δy_i, with Treated $\times$ Female gender on the vertical axis. It is only meaningful to consider the endpoints of the closed interval $[0, 1]$: for the treated females, grade outcomes improved with average income of parents. However, for the non-treated students, and for treated males (in both cases, Treated $\times$ Female gender

[13]Note that inference in the wild cluster bootstrap is based on p-values only, with the bootstrap p-value being the share of the bootstrap statistics that are more extreme than the one from the original sample. Hence, the algorithm does not produce any standard errors.

[14]We use the standardized values from Column (6), and since parental income is measured in tens of thousands of SEK, $0.010 \times 5 = 0.050$.

[15]Note that SEK 3,500,000 is slightly above the sample maximum for average parental income.

is equal to zero), academic outcomes deteriorate as parental income increases. Section V explores various potential mechanisms behind these findings.

2. Estimates for the Previous Cohort

It is important to establish that there were no spillover effects the last time the courses were given, namely during the Fall semester of 2019 when all instruction was on campus. We thus re-estimate (2) using the values for the previous cohort of students. Since it did not exist any "treated" or "untreated" students in 2019, both the treatment dummy, and the interaction term between treatment and parental income, should not be statistically different from zero. Table A.7 of Online Appendix A presents the placebo estimates. We find nothing to suggest that there were spillover effects for the previous cohort. Importantly, the triple interaction term between treatment, gender and parental income is also insignificant.

Hence, we may summarize our results so far as follows. Female students with affluent parents benefited from campus access in 2020, when EM and I students were treated with hybrid education and EP and M students had online teaching only. However, there was no socioeconomic heterogeneity with respect to grade outcomes in the 2019 cohort, when all education was given on campus. This result implies that it is the hybrid setting under blended learning that causes the socioeconomic distortions, not campus education per se.

IV.B. Difference-in-Difference Estimates: Blended Learning versus Full Campus

The hypothesis that blended learning is causing socioeconomic distortions implies that neither full campus nor full online teaching is socioeconomically distorting. It also implies that female students with affluent parents would benefit, relatively speaking, when transitioning from full campus to blended learning. We may utilize the panel structure of the data to estimate a difference-in-difference model with repeated cross-sections using both the 2019 and 2020 cohorts. Although all four student groups switched learning modes between 2019 and 2020, EP and M students went from full campus to full online, neither of which should cause socioeconomic distortions if the hypothesis outlined previously is correct. Hence, we can consider EM and I students as treated (with blended learning in the second time period), and EP and M students as untreated in this context. Using difference-in-differences has the additional advantage of allowing us to examine whether there was general grade deterioration between 2019 and 2020, in the form of a "pandemic effect" affecting all students.

Table 3 presents the results of the difference-in-difference model. First, it is notable that the interaction between time, average parental income, and female gender is negative, although it is insignificant under bootstrap correction. This suggests that for relatively wealthy students, moving away from campus classes had a negative effect on grades, but only for females. When applying the wild clustered bootstrap-corrected standard errors, only two coefficients are statistically significant, namely the triple interaction between time, treatment with hybrid education and female gender, as well as the quadruple interaction between time, treatment, female gender and average parental income. Note that the former coefficient is negative whereas the latter is positive. This means that for females with hybrid education in 2020, having sufficiently wealthy parents compensates for the negative effect captured by the interaction Time × Treated × Female gender. Finally, the results of the time-only model in Columns (1) and (3) show that there were no significant negative effects on overall grades between 2019 and 2020.

IV.C. Robustness Checks

In this subsection, we run a number of robustness checks to address possible concerns with our identification strategy.

1. Difficulty of Parallel Courses

Perhaps the main concern of our study relates to how students allocate time between courses. A feature of the design is that students take up to three courses in parallel, and parallel courses differ between programs, and hence, between treated and untreated students. Although students take 30 ECTS credits per semester regardless of program, it could be the case that some course for one of the student groups is significantly more time-consuming than it "should" be. To pass the more difficult course, students would likely allocate time away from the spillover course, the grade outcomes of which are of interest in our study. In order to check whether this was the case, we use a question of our survey asking students to estimate the share of their total study time allocated to each course. For our courses of interest, it suffices that there is no significant difference in study times between students in different programs.

Table A.8 of Online Appendix A presents the results. The p-values for the difference in mean allocated time was 0.46 for Complex Analysis (that is, between EM and EP students), and 0.64 for Supply Chain Management (I and M). Hence, we find no evidence to suggest that some of the student groups found their parallel courses disproportionally time-consuming. Although we do not explicitly ask students how many hours per week they spend studying, several university-run surveys have shown that a vast majority of students at the Faculty spend the recommended 40 hours per week (Lund University 2005; Holmström 2018).

2. Additional Robustness Checks

Besides time spent studying, it is important to ensure that both the treated and untreated students have similar opinions about how interesting their coursework is, since any heterogeneity could affect grades as well as non-grade outcomes. In our survey, we ask students to quantify on a scale from 1 to 5, how interesting each course is. By calculating the average score over treated and untreated students, with courses weighted by the number of ECTS credits, we find no difference between student groups in terms of how interesting students found their coursework.[16]

Although we have shown that there were no spillover effects for the 2019 students, it is possible that the 2019 course offerings of Complex Analysis and Supply Chain Management were an exception, and that EM and I students have higher rates of grade progression between basic and more advanced courses. This could be a concern for the causal interpretation of our findings, since it would be difficult to disentangle the effect of treatment with parallel hybrid classes during Fall 2020 from a general trend were EM and I students perform better at more advanced courses.

To exclude this possibility, we again estimate a model similar to (2), with the left-hand side replaced by the grade difference between two freshman mathematics courses for both our sampled cohorts, both taken before the pandemic. The results of this regression are presented in Table A.9 of Online Appendix A. The coefficient for EM and I, that is, the student groups that were treated with hybrid classes during Fall 2020, is close to zero in magnitude and statistically insignificant. Moreover, none of the interaction terms with second-year treatment are significant.[17] Hence, there are no signs of a general grade progression trend favoring EM and I students at the Faculty of Engineering.

Finally, since we are interested in non-grade outcomes related to campus treatment, it could be problematic if students in either the treated or untreated group had higher reported quality of life before the pandemic. Question 15 of the survey asks students to rate their pre-pandemic quality of life between 1 and 5. We regress the results on the treatment variable and its interactions with gender and the socioeconomic status index. Table A.10 of Online Appendix A presents the results. We find no indication that treated students reported higher levels of pre-pandemic satisfaction. After including the control variable for self-estimated popularity, as well as the interactions with gender and parental socioeconomy, we find that the coefficient for treatment is close to zero, and that there is no heterogeneity with respect to gender and parental socioeconomic status.

[16]The average score was 3.52 for treated students with a sample standard deviation of 2.24 (53 observations), and 3.35 for untreated students with a sample standard deviation of 2.20 (96 observations). With $N = 149$, we have $t_{147} = 0.45$, which is equivalent to a p-value of mean differences equal to 0.65.

[17]Adding cohort fixed effects has only minor effects on the magnitude of the estimated coefficients, and is available on request.

V. Evidence on Mechanisms

So far, we have established that female students with affluent parents were significantly more likely to benefit from campus treatment. We now consider the role played by network openness in explaining this finding. We are also able to exclude other potential mechanisms, such as students with parents at the higher end of the stratification hierarchy being less affected by the pandemic.

V.A. Social Networks

1. Theoretical Framework

We first examine the role played by social networks and its relationship to socioeconomic status. We start by defining network constraint, which is our primary measure of network openness. The idea is straightforward. If Alice spends all of her time with her friend Bob, a person meeting Alice also meets Bob. In this social network, the same information is shared across all members of the clique, and the network is said to suffer from a high level of network constraint. Alternatively, if Alice's friends do not know each other very well (even if they are classmates), she is more likely to access novel information when interacting with friends. This is because the first of Alice's friends gets her input from clique A, the second from clique B, and so on. Hence, Alice acts as a "broker" between networks. People linked to multiple social clusters have less information redundancy, and access to broader information, which should positively impact course performance.

We may formalize this line of thinking slightly. Let $\boldsymbol{A}$ be the square adjacency matrix associated with the social network. The elements $\{a_{ij}\}$ of $\boldsymbol{A}$ are equal to unity if individuals (vertices) i and j are connected, and zero otherwise. Here, "connected" means that there is an edge from vertex i to vertex j. Note that an individual cannot be connected to herself, implying that the graph associated with the adjacency matrix is loop-free, and $\mathrm{tr}(\boldsymbol{A}) = 0$. Denoting i's ego network by V_i, define the tie strength p_{ij} between i and j as

$$p_{ij} = \frac{a_{ij} + a_{ji}}{\sum_{k \in V_i \setminus \{i\}} (a_{ik} + a_{ki})}$$

We then calculate the network constraint (Burt 1992) associated with vertex i as

$$C_i = \sum_{k \in V_i \setminus \{i\}} \left(p_{ij} + \sum_{k \in V_i \setminus \{i,j\}} p_{iq} p_{qj} \right)^2 \tag{3}$$

Note that network constraint is undefined for isolated vertices, that is, if the vertex is not an endpoint of any edge. In our case, this would arise if the respondent did not have any friends at all. The higher the value of C_i, the higher is the constraint on i's social network. That is, an individual with a low value of C_i has a relatively low level of network constraint, and thus a more open social network, allowing the person to access different network clusters. If female students from affluent backgrounds have lower levels of network constraint, it could explain our findings on the role played by socioeconomic status for grade spillovers.[18]

2. Network Constraint and Social Stratification

Using the up to five alters named by students in question 21 of our survey, we construct two separate adjacency matrices: one for students in EM, and one for students in I. This allows us to estimate network constraint for each of the 113 students in EM and I.[19] Figure 2 shows a detail of the social network for the I students.[20] As an example of heterogeneity in network constraint, individual 86 (in the top right corner) has a relatively closed network, whereas individual 73 (in the bottom of the figure) has a considerably more open network. Using our previous notation for network constraint, $C_{73} < C_{86}$. Proceeding from here, we calculate the network constraint multiplied by 100 for each student, and estimate

$$100 \times C_i = \alpha_0 + \beta_1 \text{Inc}_i + \beta_2 \text{Gender}_i + \beta_3 \left(\text{Gender} \times \text{Inc}\right)_i + \boldsymbol{\gamma}' \boldsymbol{X}_i + \varepsilon_i \tag{4}$$

In this specification, we divide annual parental income by 10,000 to avoid extremely small numbers for the coefficient estimates. Thus, the coefficient estimate $\hat{\beta}_1$ can be interpreted as the change in network constraint associated with a SEK 10,000 increase in average annual income of parents, keeping other variables constant. Figure A.2 of Online Appendix A shows visually the relationship between network constraint and average parental income, indicating that students with high-earning parents have lower values of network constraint, and thus, more open networks.

Table 4 presents the results when estimating (4). The results confirm that both higher parental income, as well as female gender, are significantly associated with lower network constraint. Augmenting the model to include controls in Column (6) barely changes the magnitude of the coefficient estimates.

[18] We use second-year students, and previous research has shown that in 4-year degree programs, there are only minor changes in network centrality after nine months (Overgoor et al. 2020). Additionally, almost all students participate in the Faculty's orientation weeks, and peer groups formed during orientation weeks tend to be strong predictors of friendship over time (Thiemann 2021). Given this, it is unlikely that the timing between the courses of interest and our survey had any impact on the friendship networks among our sampled students.

[19] We drop a total of 14 students who transferred to Lund from other universities after the first year, or who did not actively participate in the first year.

[20] This is a so-called *directed graph*, because A naming B as one of her top 5 friends need not imply that B will name A as a top 5 friend. Consequently, there are friendship "directions".

Although the estimate of the interaction term $\hat{\beta}_1$ is statistically insignificant, the lowest values of network constraint are found only among females with wealthy parents. Figure A.3 of Online Appendix A illustrates the contour plot of fitted out-of-sample values of network constraint, with income on the horizontal axis, and the indicator for female gender on the vertical axis. Both for males and females, network constraint is decreasing with parental income, however, estimated network constraint is still significantly lower for females for any given parental income. Hence, it is likely that very low levels of network constraint, only found for female students with affluent parents, is required to overcome the significant peer communication barriers imposed by moving education away from campus.

3. Alternative Channels

In this subsection, we exclude two potential alternative reasons for the variation in network constraint among students. First, students living in affluent municipalities may be influenced by their surroundings rather than their own or their parents' social status. It could also be the case that network constraint is lower for students coming from larger cities, as these typically have more sports clubs, religious organizations, and so on, thus contributing to network openness. Table A.11 of Online Appendix A regresses, in turn, network constraint on the median income of the home municipality of each student, and the population of the home municipality. Neither the coefficient for municipality income, nor the coefficient for municipality population, are statistically significant. In addition, the explanatory power is near-zero for both specifications, further suggesting that parental income is likely to be a more plausible channel behind our findings.

V.B. Non-Grade Outcomes and Details About Channels

In this section, we use the results from our survey to examine non-grade outcomes of treatment with campus classes. These results help us exclude the possibility of our findings being driven by heterogeneity in attitudes towards the pandemic. Finally, we use the results of the survey to further investigate the mechanisms relating network constraint to realized peer interactions.

1. Non-Grade Outcomes

We use the survey results to examine whether there is heterogeneity in non-grade outcome responses depending on campus treatment. First, we ask the respondent to quantify, from 1 to 5, how negatively he or she was affected by the pandemic. The latter question focuses on the non-medical consequences of the pandemic, for instance increased boredom due to lack of social gatherings. Since education was fully online from November onward (including for treated students), we use subquestions for September–October, and

November–December.

Columns (1)–(3) of Table 5 present the results for September–October. Column (2) includes controls for pre-pandemic life satisfaction and self-estimated popularity, and Column (3) adds interactions with the standardized socioeconomic status index and female gender. Not surprisingly, students treated with campus education report lower levels of adverse mental effects amid the pandemic; around 0.35 units lower on the 1–5 scale. There was no heterogeneity with respect to gender or socioeconomic status. Columns (1)–(3) of Table A.12 of Online Appendix A show the results when the values for the second half of the semester are regressed on the same set of variables. Here, the coefficient for treatment is statistically insignificant and close to zero in magnitude. This suggests that there was no difference in self-reported mental health between student groups in the period November–December, when education for all four programs was online. This finding strongly suggests that the observed differences in self-reported mental health between treated and untreated students was indeed due to campus presence.

Columns (4)–(6) of Table 5 present the results when asking students to quantify on a scale from 1 to 5 whether he or she was worried about getting infected with the coronavirus during the first half of the semester, when some education was on campus for EM and I. The coefficient for treatment is positive and statistically significant when controlling for pre-pandemic life satisfaction and popularity in Column (5), however, it is insignificant in the full model as specified in (6). The interaction between campus treatment, female gender and the socioeconomic status index is significant and positive. This provides some support to our theory about network constraint: female students with wealthy parents seem to be aware that they are indirectly exposed to more virus transmission chains, because the openness of their social networks implies that their on-campus contacts are more likely to come from different social cliques.

2. Time Spent on Campus Outside Classes

So far, we have concluded that differences in non-grade outcomes surrounding the pandemic cannot explain why female students with affluent parents benefited from campus access in parallel courses. Instead, females and students from high-status family backgrounds have lower network constraint, which should reduce information redundancy and facilitate communication across social clusters during in-person classes. With this said, it remains a mystery why there was no income or gender effects in grade spillovers in 2019, when all education was on campus. It seems unlikely that students with affluent parents in the previous cohort had more closed networks than students in the current cohort. An alternative explanation relates to time scarcity: a sizable proportion of learning takes place outside lectures, and if female students and students with affluent parents are better at utilizing the limited campus time to plan group learning activities with peers, it would benefit their grade performance. Previous research has failed to find an association between socioeconomic status and study behaviors when education is fully on campus (Delaney et al. 2013). However, given that access to peers is limited under blended learning, these results may need to be reconsidered.

Elaborating, we ask respondents to quantify from 1 to 5 how often they studied together with their classmates for the spillover course, and whether those meetings took place in-person or online. Here, 1 means that the respondent never studied together with classmates in-person, whereas 5 means that all study sessions were in person. Since we believe that heterogeneity in campus study time may vary both with respect to treatment, gender and socioeconomic characteristics, we interact treatment both with the indicator for female gender, as well as with the standardized socioeconomic status index. The results reported in Table 6 show that the triple interaction coefficient between treatment, female gender, and socioeconomic status is significant with a p-value of 0.056. Additionally, both the coefficient for the socioeconomic status index and the interaction coefficient between treatment and female gender are significant, the latter being negative but smaller in magnitude than the triple interaction coefficient. Hence, treated females with wealthy parents spend a relatively larger share of study time meeting classmates in-person compared to treated females with less affluent parents.

We may also choose to vary only treatment status: Comparing two female students with relatively wealthy parents (say, a z-score of 2), who differ only in terms of treatment, the student treated with with blended learning will spend around 0.4 units more time studying on campus for the spillover course, based on the estimated coefficients in Table 6. Similarly, untreated male students with relatively poor parents are the group spending the least time studying with classmates on campus, which is consistent with our results on network constraint.

To summarize our findings on mechanisms, we have shown that females with affluent parents have lower network constraint compared to their peers, and consequently, higher levels of social capital. Thus, under normal circumstances, this group of students are the most efficient at network brokerage, receiving course-related input from different social cliques among their classmates. Full online instruction, on the other hand, leads to scarcity in access to peers. The adverse consequences are greater for students with *a priori* open networks, since their regular habits of interacting across social cliques are interrupted, leading to deteriorated academic outcomes. Finally, although the blended learning setting provides students with more access to peers compared to full online instruction, only a minority of students benefit academically. The relative winners of blended learning are those with broad social networks, since this group of students, being linked to different social clusters, have less information redundancy and access to broader information when communicating with peers in-class.

VI. Concluding Remarks

It remains to be seen whether the pandemic will profoundly change academic education. Globally, the supply of online courses has been increasing for several years, and multiple universities have played with the idea of replacing on-campus teaching with at least some degree of blended education, or to completely outsource curses to other universities through Massive Open Online Courses (Styles 2020).

In this paper, we show that grade outcomes under blended learning are heavily dependent both on gender and socioeconomic characteristics. In particular, partial access to campus under blended learning leads to positive grade spillovers for the online courses taken in parallel, but only for female students. The effect is increasing linearly with parental income. Conversely, both traditional in-person setting as, well as full online classes, do not cause socioeconomic distortions. We show that the relative winners of blended learning, namely female students with affluent parents, have broader social networks enabling them to take advantage of scarcely available campus time to interact with peers. However, in terms of mental health, blended learning is still preferred to full online teaching. We show that partial campus access mitigates the pandemic-related adverse effects on mental health for all students, regardless of gender or socioeconomic background.

Our findings have broader implications. For decades, intergenerational mobility has been higher for individuals with college education, suggesting that the relative benefits of higher education are skewed towards those least likely to attend college (Torche 2011). All of these studies have assumed that access to peers is fully available, with students being on campus virtually around-the-clock. If face-to-face meetings with peers become scarcely available under blended learning, these results may need to be reconsidered.

References

Alpert, William T., Kenneth A. Couch, and Oskar R. Harmon. 2016. ”A Randomized Assessment of Online Learning.” *American Economic Review* 106(5): 378–82.

Andersson, Matthew A. 2018. ”Higher Education, Bigger Networks? Differences by Family Socioeconomic Background and Network Measures.” *Socius* 4: 1–15.

Bacher-Hicks, Andrew, Joshua Goodman, and Christine Mulhern. 2021. ”Inequality in Household Adaptation to Schooling Shocks: Covid-Induced Online Learning Engagement in Real Time.” *Journal of Public Economics* 193: 104345.

Bell, Alex, Raj Chetty, Xavier Jaravel, Neviana Petkova, John Van Reenen. 2019. ”Who Becomes an Inventor in America? The Importance of Exposure to Innovation.” *Quarterly Journal of Economics* 134(2): 647–713.

Beller, Emily. 2009. ”Bringing Intergenerational Social Mobility Research into the Twenty-First Century: Why Mothers Matter.” *American Sociological Review* 74(4): 507–528.

Bettinger, Eric P., Lindsay Fox, Susanna Loeb, and Eric S. Taylor. 2017. ”Virtual Classrooms: How Online College Courses Affect Student Success.” *American Economic Review* 107(9): 2855–2875.

Black, Sandra E., Paul J. Devereux, Petter Lundborg, and Kaveh Majlesi. 2020. ”Poor Little Rich Kids? The Role of Nature versus Nurture in Wealth and Other Economic Outcomes and Behaviours.” *Review of Economic Studies* 87(4): 1683–1725.

Breza, Emily, and Arun G. Chandrasekhar. 2019. ”Social Networks, Reputation, and Commitment: Evidence from a Savings Monitors Field Experiment.” *Econometrica* 87(1): 175–216.

Bursztyn, Leonardo, Thomas Fujiwara, and Amanda Pallais. 2017. ”Acting Wife’: Marriage Market Incentives and Labor Market Investments.” *American Economic Review* 107(11): 3288–3319.

Burt, Ronald S. 1992. *Structural Holes: The Social Structure of Competition.* Cambridge, MA: Harvard University Press.

Burt, Ronald S. 2004. ”Structural Holes and Good Ideas.” *American Sociological Review* 110(2): 349–99.

Burt, Ronald S. 2017. ”Social Network and Temporal Discounting.” *Network Science* 5(4): 441–440.

Calvó-Armengol, Antoni, Eleonora Patacchini, and Yves Zenou. 2009. ”Peer Effects and Social Networks in Education.” *Review of Economic Studies* 76(4): 1239–1267.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller. 2008. ”Bootstrap-Based Improvements for Inference with Clustered Errors.” *Review of Economics and Statistics* 90(3): 414–427.

Cameron, A. Colin, and Douglas L. Miller. 2015. ”A Practitioner's Guide to Cluster-Robust Inference.” *Journal of Human Resources* 50(2): 317–372.

Chetty, Raj, John N. Friedman, Emmanuel Saez, Nicholas Turner, and Danny Yagan. 2020. ”Income Segregation and Intergenerational Mobility Across Colleges in the United States.” *Quarterly Journal of Economics* 135(3): 1567–1633.

Chetty, Raj, John N. Friedman, Nathaniel Hendren, and Michael Stepner. 2020. ”Real-time Economics: A New Platform to Track the Impacts of COVID-19 on People, Businesses, and Communities Using Private Sector Data.” NBER Working Paper no. 27431.

Cingano, Federico, and Alfonso Rosolia. 2012. ”People I Know: Job Search and Social Networks.” *Journal of Labor Economics* 30(2): 291–332.

Coleman, James S. 1988. ”Social Capital in the Creation of Human Capital.” *American Journal of Sociology* 94: S95–S120.

Conti, Gabriella, and James J. Heckman. 2010. ”Understanding the Early Origins of the Education-health Gradient: A Framework That Can Also Be Applied to Analyze Gene-environment Interactions.” *Perspectives on Psychological Science* 5(5): 585-–605.

Cornaglia, Francesca, Elena Crivellaro, and Sandra McNally. 2015. ”Mental Health and Education Decisions.” *Labour Economics* 33: 1–12.

Cruz, Cesi, Julien Labonne, and Pablo Querubín. 2017. ”Politician Family Networks and Electoral Outcomes: Evidence from the Philippines.” *American Economic Review* 107(10): 3006–3037.

De Paola, Maria, Francesca Gioia, and Vincenzo Scoppa. 2019. ”Free-riding and Knowledge Spillovers in Teams. The Role of Social Ties.” *European Economic Review* 112: 74–90.

Delaney, Liam, Colm Harmon, and Martin Ryan. 2013. ”The Role of Noncognitive Traits in Undergraduate Study Behaviours.” *Economics of Education Review* 32: 181–195.

Deming, David J., Claudia Goldin, Lawrence F. Katz, and Noam Yuchtman. 2015. ”Can Online Learning Bend the Higher Education Cost Curve?” *American Economic Review* 105(5): 496–501.

Eisenberg, Daniel, Ezra Golberstein, and Justin B. Hunt. 2009. ”Mental Health and Academic Success in College.” *B.E. Journal of Economic Analysis & Policy* 9(1): 40.

El-Khatib, Rwan, Kathy Fogel, and Tomas Jandik. 2015. ”CEO Network Centrality and Merger Performance.” *Journal of Financial Economics* 116(2): 349–382.

Figlio, David, Mark Rush, and Lu Yin. 2013. ”Is It Live or Is It Internet? Experimental Estimates of the Effects of Online Instruction on Student Learning.” *Journal of Labor Economics* 31(4): 763–84.

Goodman, Joshua, Julia Melkers, and Amanda Pallais. 2019. ”Can Online Delivery Increase Access to Education?” *Journal of Labor Economics* 37(1): 1–34.

Granovetter, Mark. 1985. ”Economic Action and Social Structure: The Problem of Embeddedness.” *American Journal of Sociology* 91(3): 481–510.

Holmström, Ola. 2018. ”Studentbarometern 2017” [The Student Survey 2017]. Lund University Registrar’s Office, unnumbered report.

Husky, Mathilde M., Viviane Kovess-Masfety, and Joel D. Swendsen. 2020. ”Stress and Anxiety Among University Students in France During Covid-19 Mandatory Confinement.” *Comprehensive Psychiatry* 102: 152191.

Kecojevic, Aleksandar, Corey H. Basch, Marianne Sullivan, and Nicole K. Davi. 2020. ”The Impact of the COVID-19 Epidemic on Mental Health of Undergraduate Students in New Jersey, Cross-Sectional Study.” *PLoS ONE* 15(9): e0239696.

Kim, Young K., and Linda J. Sax. 2009. ”Student–Faculty Interaction in Research Universities: Differences by Student Gender, Race, Social Class, and First-Generation Status.” *Research in Higher Education* 50: 437–459.

Kohn, Melvin L., Kazimierz Slomczynski, and Carrie Schoenbach. 1986. ”Social Stratification and the Transmission of Values in the Family: A Cross-National Assessment.” *Sociological Forum* 1: 73–102.

Kossinets, Gueorgi. 2006. ”Effects of Missing Data in Social Networks.” *Social Networks* 28(3): 247–268.

Kozakowski, Whitney. 2019. ”Moving the Classroom to the Computer Lab: Can Online Learning with In-Person Support Improve Outcomes in Community Colleges?” *Economics of Education Review* 70: 159–172.

Lindquist, Matthew L., Joeri Sol, and Mirjam Van Praag. 2015. ”Why Do Entrepreneurial Parents Have Entrepreneurial Children?” *Journal of Labor Economics* 33(2): 269–296.

Lund University. 2005. ”Teknologer och civilingenjörer: Erfarenheter av utbildningen vid LTH” [Engineering students: Experience from the education at the Faculty of Engineering]. Lund University Registrar’s Office Report 2005:234.

Lutter, Mark. 2015. ”Do Women Suffer from Network Closure? The Moderating Effect of Social Capital on Gender Inequality in a Project-Based Labor Market, 1929 to 2010.” *American Sociological Review* 80(2): 329–358.

Mare, Robert D. 2015. ”Measuring Networks Beyond the Origin Family.” *Annals of the American Academy of Political and Social Science* 657(1): 97–107.

Mengel, Friederike. 2020. ”Gender Differences in Networking.” *Economic Journal* 130(630): 1842–1873.

Mullainathan, Sendhil, and Eldar Shafir. 2013. *Scarcity: Why Having Too Little Means So Much*. New York: Henry Holt and Company.

Opper, Sonja, and Ronald S. Burt. 2021. ”Social Network and Temporal Myopia.” *Academy of Management Journal*, forthcoming.

Overgoor, Jan, Bogdan State, and Lada Adamic 2020. ”The Dynamics of U.S. College Network Formation on Facebook.” Working Paper, Stanford University.

Patsali, Mikaella E., Danai-Priskila V. Mousa, Eleni V.K. Papadopoulou, Konstantina K.K. Papadopoulou, Chrysi K. Kaparounaki, Ioannis Diakogiannis, and Konstantinos N. Fountoulakis. 2020. ”University Students’ Changes in Mental Health Status and Determinants of Behavior During the COVID-19 Lockdown in Greece.” *Psychiatry Research* 292: 113298.

Sandström, David. 2020. ”Info undersöker. Den årliga undersökningen från Info! Wihoo!” ['Info' explores. Info's yearly poll! Wihoo!] *I-type* 40: 16–17.

Smith, Michelle, William B. Wood, Wendy Adams, Carl E. Wieman, Jennifer K. Knight, Nancy Guild, and Tin Tin Su. 2009. ”Why Peer Discussion Improves Student Performance on In-Class Concept Questions.” *Science* 323(5910): 122–124.

Smith, Jeffrey A., and James Moody. 2013. ”Structural Effects of Network Sampling Coverage I: Nodes Missing at Random.” *Social Networks* 35(4): 652–668.

Springer, Leonard, Mary Elizabeth Stanne, and Samuel S. Donovan. 1999. ”Effects of Small-Group Learning on Undergraduates in Science, Mathematics, Engineering, and Technology: A Meta-Analysis.” *Review of Educational Research* 69(1): 21–51.

Styles, Aja. 2020. ”'A Scam': Fears Over Increased Outsourced Learning at Murdoch University.” *WAtoday*, November 10.

Thiemann, Petra. 2021. ”The Persistent Effects of Short-Term Peer Groups on Performance: Evidence from a Natural Experiment in Higher Education.” *Management Science*, forthcoming.

Torche, Florencia. 2011. ”Is a College Degree Still the Great Equalizer? Intergenerational Mobility across Levels of Schooling in the United States.” *American Journal of Sociology* 117(3): 763–807.

Webb, Matthew D. 2013. ”Reworking Wild Bootstrap Based Inference For Clustered Errors.” Working Paper 1315, Economics Department, Queen's University.

Table 1

Course structure, fall semester, second year

Course name	Subject classification	Sep–Oct	Nov–Dec
Microeconomic Theory (C, 6)	Economics	EM, I	
Complex Analysis (O, 7)	Mathematics	EM, EP	
Supply Chain Management (O, 5)	Operations Management	I	M
Mathematical Statistics (O, 9)	Mathematics	EM, I	EM, I
Systems and Transforms (O, 7)	Mathematics		EM, EP
Dynamics (O, 6)	Physics	EP	
Mechanics (O, 15)	Physics	M	M
Solid Mechanics (O, 4.5)	Physics		EP
Statistical Thermodynamics (O, 6)	Physics	EP	EP
Thermodynamics and Fluid Mechanics (O, 11)	Physics	M	M
Marketing and Globalization (O, 4.5)	Business Administration		I
Programming (O, 4.5)	Computer Science		I

Note. Mandatory courses during the Fall semester for second-year students enrolled in Engineering Mathematics (EM), Engineering Physics (EP), Industrial Engineering (I), and Mechanical Engineering (M). Spillover courses underlined. In brackets: ”C” and ”O” denote campus and online courses, respectively, whereas the number refers to number of ECTS credits awarded for passing the course in question.

Table 2
Main results

	Unadjusted clustered standard errors			Bootstrap-adjusted clustered standard errors		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.157	0.116	0.085	0.157	0.116	0.085
	(0.300)	(0.381)	(0.352)	[0.698]	[0.812]	[0.866]
Average parental income		−0.001	−0.001*		−0.001	−0.001
(SEK, 10,000s)		(0.001)	(0.000)		[0.688]	[0.238]
Female gender		0.077	0.069		0.077	0.069
		(0.424)	(0.367)		[0.700]	[0.806]
Treated		0.000	0.000		0.000	0.000
× Average parental income		(0.001)	(0.001)		[0.968]	[0.740]
Treated		−0.613	−0.583		−0.613	−0.538
× Female gender		(0.443)	(0.399)		[0.210]	[0.122]
Average parental income		−0.004	−0.004		−0.004	−0.004
× Female gender		(0.004)	(0.003)		[0.746]	[0.502]
Treated × Female gender		0.011*	0.010*		0.011*	0.010*
× Average parental income		(0.004)	(0.004)		[0.076]	[0.076]
Student characteristic controls	No	No	Yes	No	No	Yes
Observations	320	320	318	320	320	318
Mean dep. var.	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.006	0.027	0.038	0.006	0.027	0.038

Note. Dependent variable: Change in achieved grade between spillover course and equivalent first-year course. A constant is included in all regressions. Columns (1), (2), (4), and (5): No controls. Columns (3) and (6): Controls for age, non-Western background of parents, and median income of home municipality. Standard errors clustered by program in brackets, with Columns (4)–(6) reporting wild cluster bootstrap-adjusted p-values in square brackets, computed using 500 replications and bootstrap weights drawn from the Webb distribution. * denotes significance at the 10% level.

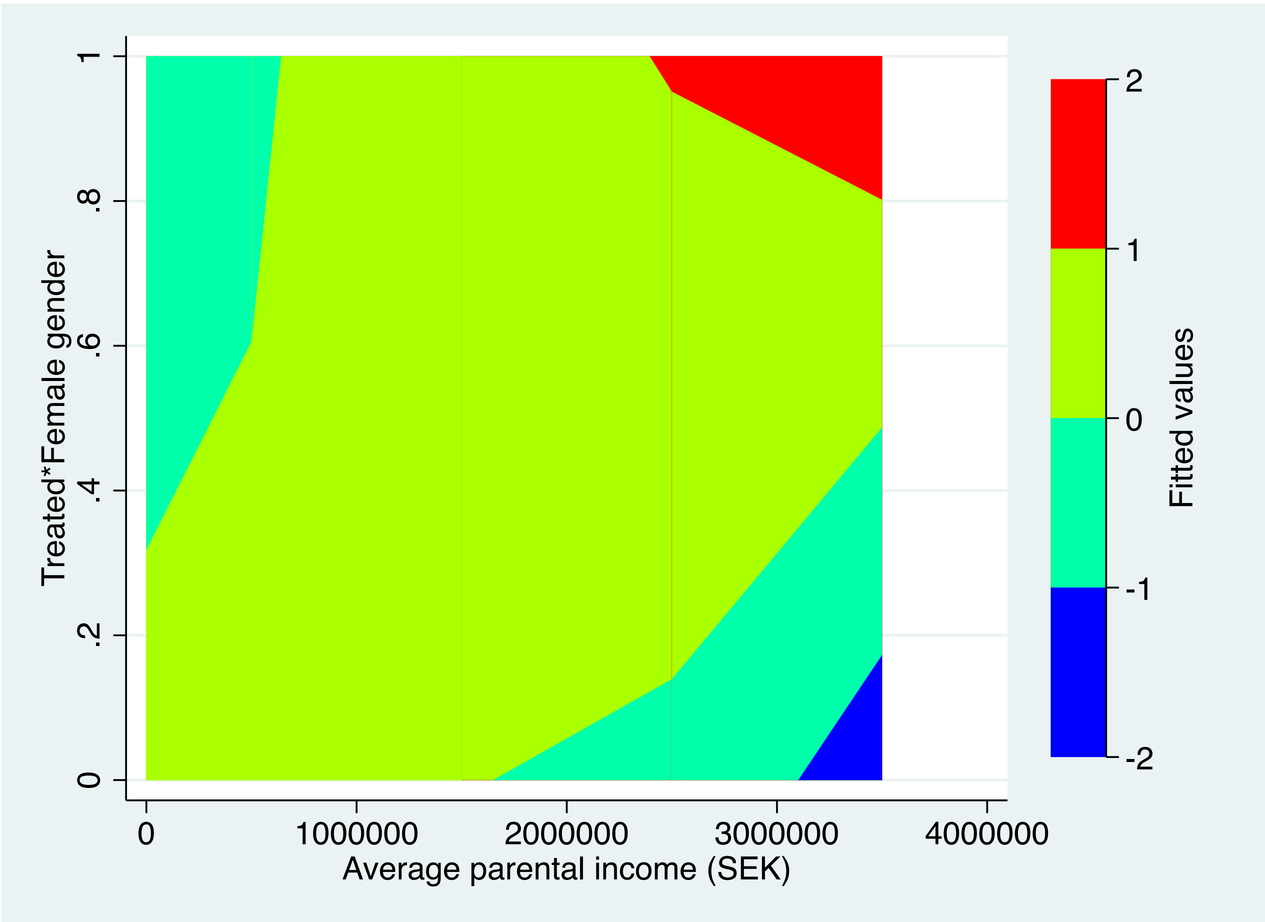


Figure 1: Contour plot of the predicted standardized values of Δy_i, with average parental income on the horizontal axis and Treated $\times$ Female gender on the vertical axis.

Table 3
Difference-in-difference estimates

	Unadjusted clustered standard errors		Bootstrap-adjusted clustered standard errors	
	(1)	(2)	(3)	(4)
Time	−0.174	−0.096	−0.174	−0.096
	(0.190)	(0.291)	[0.468]	[0.800]
Treated		0.075		0.075
		(0.267)		[0.822]
Average parental income (SEK, 10,000s)		0.000		0.000
		(0.001)		[0.782]
Female gender		−0.473**		−0.473
		(0.114)		[0.392]
Time × Treated		0.020		0.020
		(0.278)		[0.924]
Time × Average parental income		−0.001		−0.001
		(0.001)		[0.644]
Time × Female gender		0.547		0.547
		(0.320)		[0.128]
Treated × Average parental income		0.000		0.000
		(0.002)		[0.980]
Treated × Female gender		0.423*		0.423
		(0.144)		[0.160]
Average parental income × Female gender		0.006*		0.006
		(0.003)		[0.922]
Time × Treated × Average parental income		0.001		0.001
		(0.002)		[0.720]
Time × Treated × Female gender		−1.143**		−1.143**
		(0.359)		[0.032]
Time × Average parental income × Female gender		−0.011***		−0.011
		(0.002)		[0.170]
Treated × Female gender × Average parental income		−0.004		−0.004
		(0.003)		[0.642]
Treated × Female gender × Average parental income		−0.004		−0.004
		(0.003)		[0.642]
Time × Treated × Female gender × Average parental income		0.017***		0.017**
		(0.002)		[0.050]
Student characteristic controls	No	Yes	No	Yes
Observations	562	560	562	560
Mean dep. var.	0.000	0.000	0.000	0.000
R^2	0.008	0.039	0.008	0.039

Note. Dependent variable: Change in achieved grade between spillover course and equivalent first-year course. A constant is included in all regressions. Columns (1) and (3): No controls. Columns (2) and (4): Controls for age, non-Western background of parents, and median income of home municipality. Standard errors clustered by program in brackets, with Columns (3)–(4) reporting wild cluster bootstrap-adjusted p-values in square brackets, computed using 500 replications and bootstrap weights drawn from the Webb distribution. ** and *** denote significance at the 5% and 1% level, respectively.

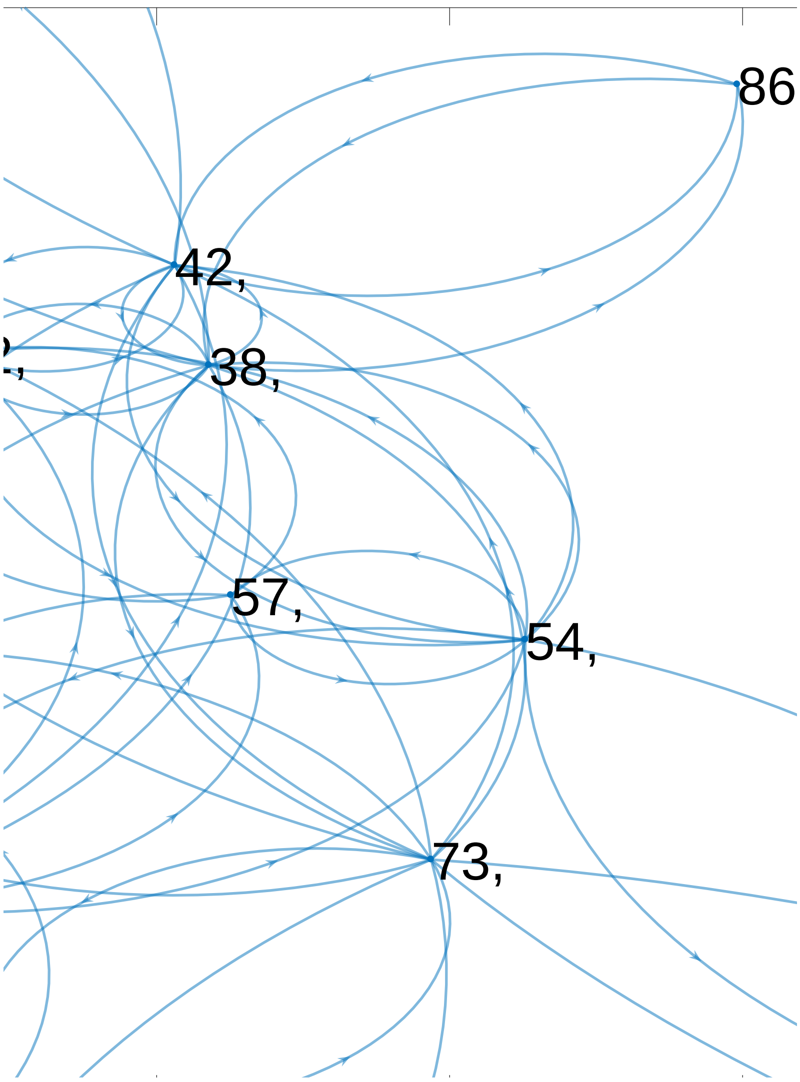


Figure 2: Detail of the estimated social network for the I students.

Table 4
Network constraint, gender, and parental income

	(1)	(2)	(3)	(4)	(5)	(6)
Average parental income (SEK, 10,000s)	-0.102^{***}		-0.097^{***}		-0.073^{*}	-0.091^{*}
	(0.029)		(0.029)		(0.042)	(0.047)
Female gender		-12.209^{***}	-11.171^{***}		-11.973^{***}	-11.676^{***}
		(4.045)	(3.855)		(3.844)	(4.022)
Average parental income (SEK, 10,000s)				-0.157^{***}	-0.074	-0.072
× Female gender				(0.039)	(0.065)	(0.069)
Student characteristic controls	No	No	No	No	No	Yes
Observations	113	113	113	113	113	113
Mean dep. var.	58.528	58.528	58.528	58.528	58.528	58.528
R^2	0.063	0.068	0.125	0.048	0.132	0.141

Note. Dependent variable: Network constraint (×100). A constant is included in all regressions. Columns (1)–(5): No controls. Column (6): Controls for age, non-Western background, and median income of home municipality. Heteroscedasticity-robust standard errors in brackets. * and *** denote significance at the 10% and 1% level, respectively.

Table 5

Non-grade outcomes, Sep–Oct (bootstrap)

	Adverse mental effects			Afraid of contracting virus		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-0.353^{**}	-0.471^{**}	-0.526^{**}	-0.026	0.125^{**}	-0.019
	[0.050]	[0.048]	[0.050]	[0.698]	[0.048]	[0.902]
Socioeconomic status index			-0.004			-0.027
			[0.938]			[0.670]
Female gender			0.361			-0.321
			[0.154]			[0.298]
Treated			0.096			0.128
× Socioeconomic status index			[0.670]			[0.730]
Treated			-0.091			0.147
× Female gender			[0.726]			[0.350]
Socioeconomic status index			-0.294			-0.141
× Female gender			[0.698]			[0.766]
Treated × Female gender			0.344			0.537^{*}
× Socioeconomic status index			[0.598]			[0.070]
Student characteristic controls	No	Yes	Yes	No	Yes	Yes
Observations	150	135	135	150	135	135
Mean dep. var.	2.81	2.81	2.81	1.96	1.96	1.96
R^2	0.024	0.045	0.083	0.000	0.058	0.100

Note. Dependent variable: ”How was your mental health affected by the pandemic”, and ”How worried were you about contracting COVID-19”, respectively. Both variables are measured on a scale from 1 to 5, for the period September–October. A constant is included in all regressions. Columns (1) and (4): No controls. Columns (2)–(3) and (5)–(6): Controls for pre-pandemic life satisfaction and self-estimated popularity. P-values are in square brackets and computed using wild cluster bootstrap with 500 replications, with bootstrap weights drawn from the Webb distribution. * and ** denote significance at the 10% and 5% level, respectively.

Table 6
Self-estimated study time on campus

	(1)	(2)	(3)
Treated	0.068	−0.127	−0.006
	[0.772]	[0.668]	[0.970]
Socioeconomic status index			0.309*
			[0.072]
Female gender			0.793
			[0.276]
Treated			−0.435
× Socioeconomic status index			[0.196]
Treated			−0.600*
× Female gender			[0.098]
Socioeconomic status index			−0.834
× Female gender			[0.330]
Treated × Female gender			0.927*
× Socioeconomic status index			[0.056]
Student characteristic controls	No	Yes	Yes
Observations	151	135	135
Mean dep. var.	2.179	2.179	2.179
R^2	0.001	0.122	0.229

Note. Dependent variable: "On a scale from 1 to 5, where 1 is almost never, and 5 is daily, how often did you study together with your classmates when studying Complex Analysis or Supply Chain Management? Now, we mean physical meetings only." A constant is included in all regressions. Column (1): No controls. Columns (2)–(3): Controls for pre-pandemic life satisfaction, self-estimated popularity and estimated interest in the spillover course on a scale from 1 to 5. P-values are in square brackets and computed using wild cluster bootstrap with 500 replications, with bootstrap weights drawn from the Webb distribution. * denotes significance at the 10% level, respectively.

Online Appendix [Not for Publication]

A. Additional Empirical Results

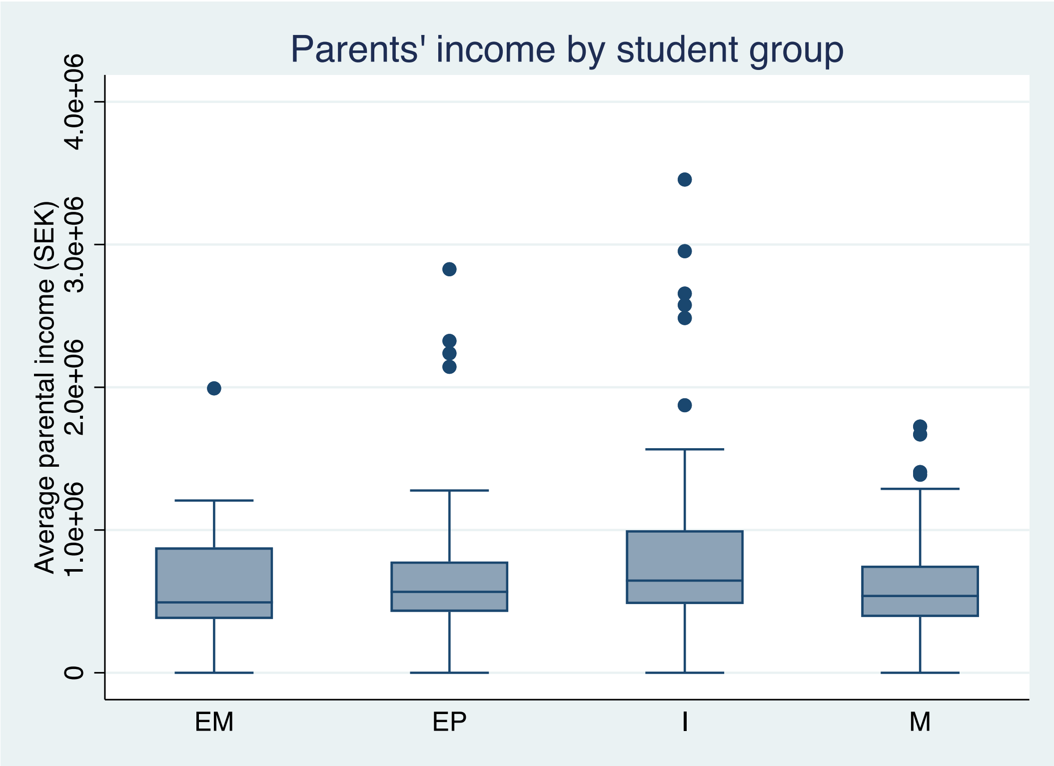


Figure A.1: Box-and-whisker diagram of average annual parental income in 2019 measured in millions of SEK for each of the four student groups: Engineering Mathematics (EM), Engineering Physics (EP), Industrial Engineering (I), and Mechanical Engineering (M).

Table A.1
Course structure, first year

Subject classification	EM	EP	I	M	Comments
Mathematics	28.5	28.5	27	27	Divided into 15 credits single variable calculus, 6 linear algebra, 6 multivariable calculus. An additional 1.5 credits multivariable calculus is added for EM and EP students.
Physics	13.5	22.5	18	6	
Programming	18	9		12	
Operations Management			9	9	
Business Administration			6		
Mechanical Engineering				6	
Overall first year	60	60	60	60	

Note. First-year course structure for the four engineering programs evaluated in the experiment. The numbers refer to ECTS (European Credit Transfer System) credits. Note that 1.5 ECTS credits is equal to one week (40 hours) of full-time studies. Overall, 60 ECTS corresponds to a total workload of 1600 hours per annum. All courses are mandatory for students in each program.

Table A.2
Balance tests, survey

Student characteristic	Full sample	Survey sample	p-value for equality of proportions/means
Treated (%)	39.0	35.8	[0.50]
Female (%)	27.6	32.4	[0.28]
Median income of home municip. (SEK, thousands)	337.29	334.48	[0.49]

Note. Self-estimated study time (in percent) allocated to Complex Analysis (for EM and EM), and Supply Chain Management (for I and M) with standard errors in brackets. The column entitled "F-stat" refers to the F-statistic for the difference in means between the treated and untreated student groups, with p-values in square brackets.

Table A.3
Construction of the socioeconomic status index

Question number	Statement	Alternative	Score
2	In which municipality did you live at the time of your graduation from high school?	290 municipalities	Range: [2.78, 4.43] (the variable Median income of home municipality divided by 100)
3	When growing up, in what type of dwelling did you mainly live?	House	4
		Townhouse	3
		Housing cooperative	2
		Rental apartment	1
4	Does anyone of your parents have a college or university degree?	Yes, both	3
		Yes, but only one parent.	2
		No	1
5	Has anyone of your parents been the CEO or a board member of a publicly listed company?	Yes	4
		No	1
		Don't know	1

Note. The table shows, for each question, the contribution of each response to the socioeconomic status index for student i.

Table A.4
CEO position or board assignment of parents, 2019

Id	Gender	Taxable income (SEK, 2019)	Current assignments (2019)
1	M	5,654,100	1×CEO, 1×board member
2	W	5,241,400	4×CEO, 7×board member
3	M	4,982,400	4×board member
4	M	4,906,000	3×board member
5	M	4,432,000	2×CEO, 3×board member
6	M	3,987,700	1×CEO, 3×board member
7	M	3,857,500	1×board member
8	M	3,602,600	*no current or previous assignments in Sweden*
9	M	3,445,200	*no current or previous assignments in Sweden*
10	W	3,063,200	1×CEO, 2×board member
11	M	3,047,500	1×CEO, 15×board member
12	M	2,839,700	1×board member
13	M	2,652,000	*no current assignment*; until 2003: 1×board member
14	W	2,484,600	1×board member
15	M	2,453,100	7×board member
16	M	2,316,300	*no current or previous assignments in Sweden*
17	W	2,253,800	3×board member
18	M	2,231,500	*no current or previous assignments in Sweden*
19	M	2,022,500	2×board member
20	M	1,937,200	2×CEO, 2×board member

Note. The table shows, for the 20 highest earning parents, whether the individual is a CEO, or has any current (2019) board assignments. If the person had no CEO position or board assignments in 2019, the table shows the year of the last registered CEO position or board assignment.

Table A.5
Summary statistics

Main outcome variable	Mean	Std.dev.	Min	Max
Grade difference (Δy_i)	−0.058	1.712	−5	4
Second-year grade variable				
Grade, Supply Chain Management	3.983	0.591	3	5
Grade, Complex Analysis	4.000	0.793	3	5
First-year grade variables				
Grade, Operations Management	3.787	0.794	3	5
First-year mathematics GPA	3.998	0.709	3	5
Student-specific variables				
Average parental income (SEK)	679,296.1	463,433.6	0	3,455,200
Female gender	0.276	0.448	0	1
Age	21.045	1.089	19	28
Non-Western background of parents	0.063	0.243	0	1
Median income of home municip. (SEK) (thousands, SEK)	337.291	41.333	278.1	443.1

Note. The variable Grade difference is the difference between the second-year grade in Supply Chain Management and first-year grade in Operations Management for I and M students, and the difference between the grade in Complex Analysis and first-year mathematics GPA for EM and EP students.

Table A.6
Summary statistics: 2019 cohort

Main outcome variable	Mean	Std.dev.	Min	Max
Grade difference (Δy_i)	0.164	0.844	-5	2
Second-year grade variable				
Grade, Supply Chain Management	4.317	0.778	3	5
Grade, Complex Analysis	3.958	0.815	3	5
First-year grade variables				
Grade, Operations Management	3.963	0.795	3	5
First-year mathematics GPA	4.013	0.698	3	5
Student-specific variables				
Average parental income (SEK)	693,571.1	502,553.0	0	4,040,300
Female gender	0.374	0.485	0	1
Age	21.164	1.262	19	29
Non-Western background of parents	0.046	0.209	0	1
Median income of home municip. (thousands, SEK)	339.585	41.035	278.1	443.4

Note. The variable Grade difference is the difference between the second-year grade in Supply Chain Management and first-year grade in Operations Management for I and M students, and the difference between the grade in Complex Analysis and first-year mathematics GPA for EM and EP students.

Table A.7
Main results, 2019 cohort

	(1)	(2)	(3)
Treated	0.186	0.152	0.250
	[0.644]	[0.706]	[0.658]
Average parental income		−0.001	−0.001
(SEK, 10,000s)		[0.800]	[0.810]
Female gender		−0.739	−0.705
		[0.208]	[0.276]
Treated		−0.001	−0.002
× Average parental income		[0.738]	[0.746]
Treated		0.616	0.472
× Female gender		[0.162]	[0.154]
Average parental income		0.010	0.010
× Female gender		[0.738]	[0.746]
Treated × Female gender		−0.006	−0.005
× Average parental income		[0.588]	[0.566]
Student characteristic controls	No	No	Yes
Observations	242	242	242
Mean dep. var.	0.000	0.000	0.000
R^2	0.001	0.039	0.061

Note. Dependent variable: Change in achieved grade between spillover course and equivalent first-year course, 2019 cohort. A constant is included in all regressions. Columns (1) and (2): No controls. Column (3): Controls for age, non-Western background of parents, and median income of home municipality. P-values are in square brackets and computed using wild cluster bootstrap with 500 replications, with bootstrap weights drawn from the Webb distribution. * denotes significance at the 10% level.

Table A.8
Share of study time allocated to courses

Course	Treated groups	Untreated groups	F-stat.	*N*
Complex Analysis	50.417	54.400	–0.55	53
	(5.092)	(1.769)	[0.46]	
Supply Chain Management	23.048	22.018	0.22	98
	(1.465)	(1.511)	[0.64]	
N	54	97		

Note. Self-estimated study time (in percent) allocated to Complex Analysis (for EM and EM), and Supply Chain Management (for I and M) with standard errors in brackets. The column entitled "F-stat" refers to the F-statistic for the difference in means between the treated and untreated student groups, with *p*-values in square brackets.

Table A.9
Spillover effects, first year

	(1)	(2)
Treated	0.060	0.158
	[0.710]	[0.664]
Average parental income		0.004
(SEK, 10,000s)		[0.298]
Female gender		−0.018
		[0.824]
Treated		−0.002
× Average parental income		[0.418]
Treated		0.166
× Female gender		[0.584]
Average parental income		−0.001
× Female gender		[0.886]
Treated × Female gender		−0.001
× Average parental income		[0.584]
Student characteristic controls	No	Yes
Observations	464	462
Mean dep. var.	0.000	0.000
R^2	0.001	0.024

Note. Dependent variable: Change in achieved grade between second semester and first semester mathematics courses for both cohorts. A constant is included in all regressions. Column (1): No controls. Column (2): Controls for age, non-Western background of parents, and median income of home municipality. P-values are in square brackets and computed using wild cluster bootstrap with 500 replications, with bootstrap weights drawn from the Webb distribution. * denotes significance at the 10% level.

Table A.10
Pre-pandemic satisfaction

	(1)	(2)
Treated	0.133	0.036
	[0.132]	[0.794]
Socioeconomic status index		−0.036
		[0.358]
Female gender		0.018
		[0.690]
Treated		−0.056
× Socioeconomic status index		[0.788]
Treated		−0.007
× Female gender		[0.946]
Socioeconomic status index		−0.002
× Female gender		[0.934]
Treated × Female gender		−0.130
× Socioeconomic status index		[0.688]
Student characteristic controls	No	Yes
Observations	149	135
Mean dep. var.	4.07	4.07
R^2	0.006	0.053

Note. Dependent variable: "On a scale from 1 to 5, where 1 is very dissatisfied, and 5 is very satisfied, how satisfied were you with the quality of your life during the period immediately before the onset of the pandemic (February/March 2020)? Here, we mean well-being broadly speaking, joy of life, view of the future, and so on." A constant is included in all regressions. Column (1): No controls. Column (2): Control for self-estimated popularity. P-values are in square brackets and computed using wild cluster bootstrap with 500 replications, with bootstrap weights drawn from the Webb distribution. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.11
Network constraint: Alternative channels

	(1)	(2)
Panel A:		
Median income of home municipality (SEK, thousands)	−0.013	−0.010
	(0.044)	(0.046)
R^2	0.001	0.003
Panel B:		
Population of home municipality (thousands)	−0.001	−0.001
	(0.008)	(0.008)
R^2	0.000	0.003
Student characteristic controls	No	Yes
Observations	113	113
Mean dep. var.	58.528	58.528

Note. Dependent variable: Network constraint ($\times 100$). A constant is included in all regressions. Column (1): No controls. Column (2), Panel A: Controls for age, and non-Western background of parents. Column (2), Panel B: Controls for age, non-Western background of parents, and median income of home municipality. Heteroscedasticity-robust standard errors in brackets.

Table A.12
Non-grade outcomes, Nov–Dec (bootstrap)

	Adverse mental effects			Afraid of contracting virus		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-0.179	-0.086^{*}	-0.296	-0.026	0.125^{**}	0.223
	[0.468]	[0.086]	[0.440]	[0.698]	[0.048]	[0.464]
Socioeconomic status index			-0.183			0.092
			[0.188]			[0.782]
Female gender			0.534			0.622
			[0.204]			[0.214]
Treated			-0.184			-0.314
× Socioeconomic status index			[0.428]			[0.286]
Treated			-0.083			-0.205
× Female gender			[0.654]			[0.774]
Socioeconomic status index			-0.411			-0.090^{*}
× Female gender			[0.756]			[0.100]
Treated × Female gender			0.035			0.745
× Socioeconomic status index			[0.876]			[0.464]
Student characteristic controls	No	Yes	Yes	No	Yes	Yes
Observations	149	134	134	150	135	135
Mean dep. var.	3.53	3.53	3.53	2.63	2.63	2.63
R^2	0.006	0.034	0.093	0.000	0.058	0.126

Note. Dependent variable: "How was your mental health affected by the pandemic", and "How worried were you about contracting COVID-19", respectively. Both variables are measured on a scale from 1 to 5, for the period November–December. A constant is included in all regressions. Columns (1) and (4): No controls. Columns (2)–(3) and (5)–(6): Controls for pre-pandemic life satisfaction and self-estimated popularity. P-values are in square brackets and computed using wild cluster bootstrap with 500 replications, with bootstrap weights drawn from the Webb distribution. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

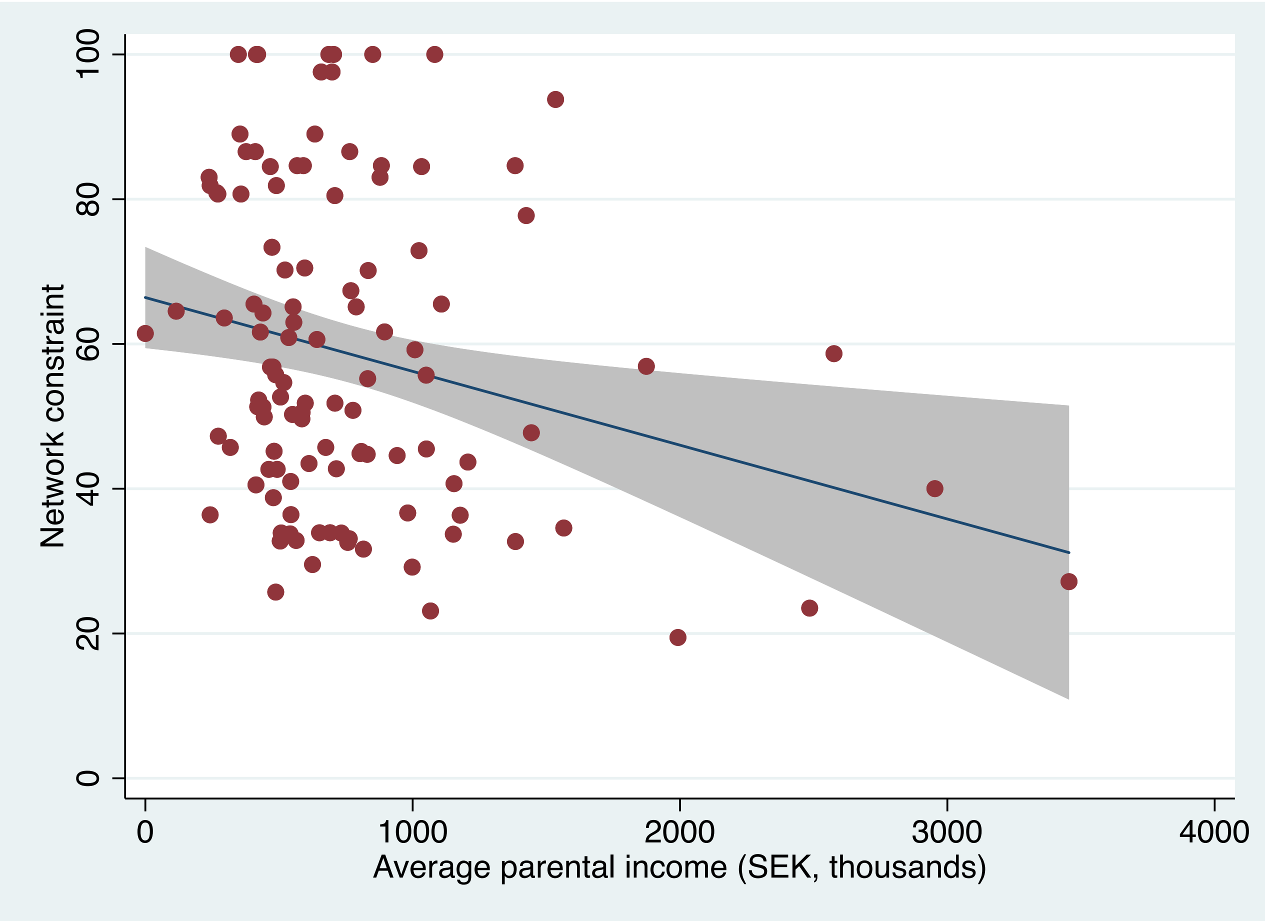


Figure A.2: Scatter plot of the relationship between average parental income on the horizontal axis and network constraint (× 100) on the vertical axis, with 95% confidence bands around the estimated regression line.

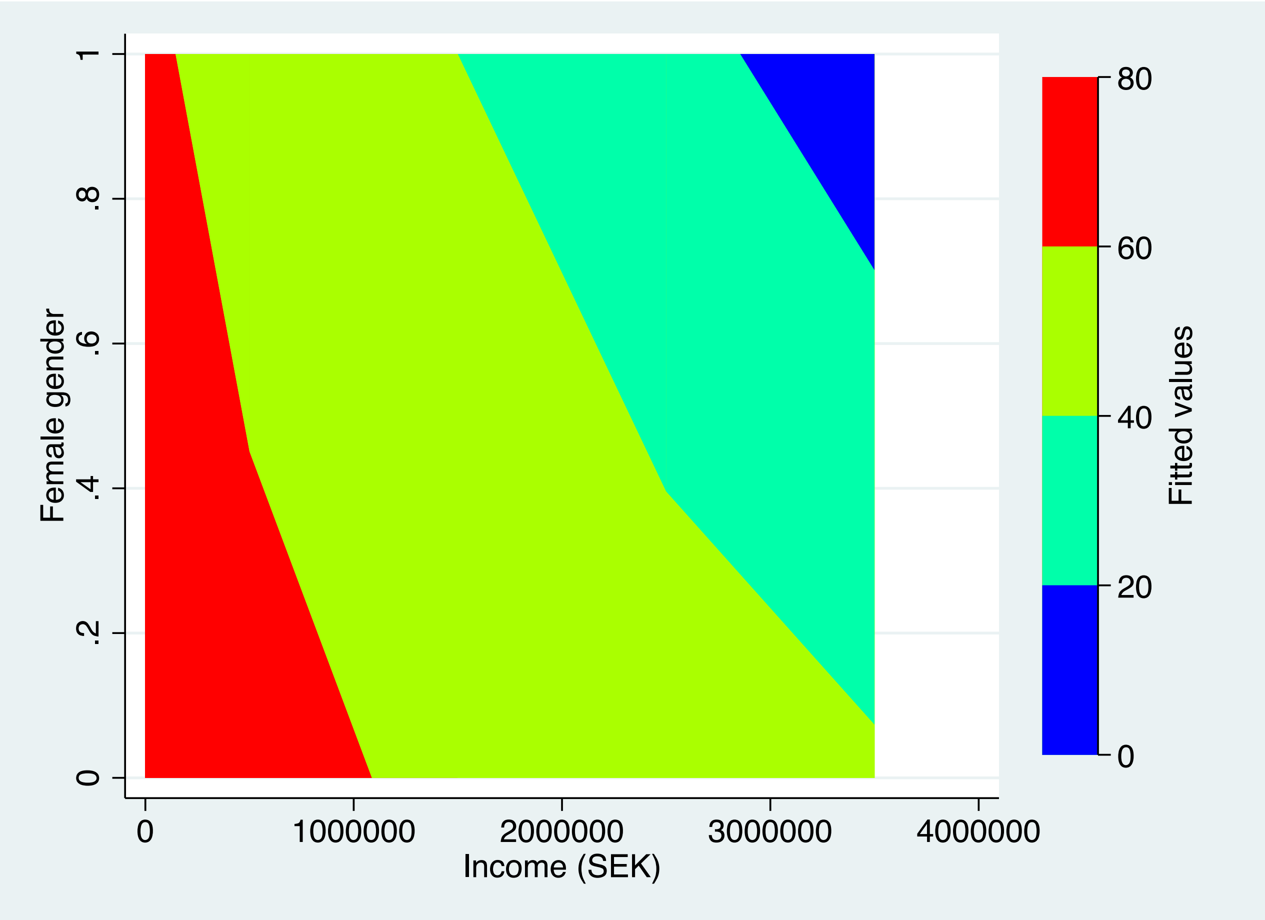


Figure A.3: Contour plot of the values of network constraint, with average parental income on the horizontal axis the indicator for female gender on the vertical axis.

B. Data Description

B.A. Data Sources

This subsection describes the construction of the variables used in the empirical analysis in additional detail.

Academic outcomes. All grade data comes from LADOK, which is the student administration system used at Lund University.

Parental income. To obtain the data on parents' income, we first retrieved the personal identity numbers (social security numbers) of both parents using the population registry. Then, we proceeded by using the Tax Agency's data on taxable income for the latest available year, 2019.[21] This figure includes earned income, but excludes capital gains. In accordance with the Swedish Constitution, both the personal identity numbers and the tax records are publicly available information.

Additional personal data. Using the population registry, it is straightforward to retrieve additional demographic characteristics for our sampled students. In this paper, we use gender, whether both parents were born in a non-Western nation, as well as the name of the municipality where students resided before starting university. The penultimate digit in the 12-digit personal identity number gives the gender at birth, being odd for men and even for women.

Municipality median income and population. As a control variable in our regressions in Section III, we use the median disposable income for each municipality for the latest available year, 2018, and for individuals aged 20–64. In Section IV, we additionally utilize data on the population size of students' home municipalities for robustness checks. The data source for both of these variables is the Swedish Statistics Agency.

Parental CEO and/or board assignments. The robustness check presented in Table A.4 of Online Appendix A confirms that most of the wealthiest parents had either a CEO position or board assignment in 2019. This data comes from the Swedish Companies Registration Office, a government agency.

[21] In the robustness checks for the previous cohort, we used tax records from 2018.

B.B. Some Notes on the Socioeconomic Status Index

In this subsection, we state and prove a result on the theoretical lower and upper bounds on the socioeconomic status index discussed in Section III.C.

Theorem B.1. *Given the 2018 values of the median disposable income of municipalities, the theoretical minimum value for the socioeconomic status index is 5.78, and the maximum value is 15.43.*

Proof. Consider first the lower bound, which corresponds to a student from the poorest municipality obtaining the lowest score in each of the four questions. Summing the lowest values according to equation (1), gives $2.78+1+1+1 = 5.78$. Similarly, the upper bound corresponds to a student from the wealthiest municipality obtaining the highest score in each of the four questions. This gives $4.43 + 4 + 3 + 4 = 15.43$. QED

C. Survey Construction

The following section describes each question used in our survey in additional detail.

1. What is your gender?

- [ ] Male
- [ ] Female
- [ ] Prefer not to specify.

2. In which municipality did you live at the time of your graduation from high school?

____

3. When growing up, in what type of dwelling did you mainly live?

- [ ] House
- [ ] Housing cooperative
- [ ] Rental apartment
- [ ] Townhouse

4. Does anyone of your parents have a college or university degree?

- [ ] Yes, both.
- [ ] Yes, but only one parent.
- [ ] No

5. Has anyone of your parents been the CEO or a board member of a publicly listed company?

- [ ] Yes
- [ ] No
- [ ] Don't know.

6. Much of last semester[22] was online. Did you at any point during the semester move back to live with your parents because of this?

- [ ] Yes
- [ ] No
- [ ] I already live with my parents.

[22] Refers to Fall 2020.

7. During the period September–October[23] last semester, how large a share (in %) of your total time spent studying, did you spend on each of the following courses? By ”time spent studying”, we mean the sum of lectures, exercise sessions, self-study, exam cramming, and so on. It should sum to 100.

[insert course 1][24]
[insert course 2]
[insert course 3]

8. On a scale from 1 to 5, where 1 is very uninteresting, and 5 is super-interesting, how would you rate each of the following courses?

[insert course 1]
[insert course 2]
[insert course 3]

9. On a scale from 1 to 5, where 1 is almost never, and 5 is daily, how often did you study together with your classmates when studying the following courses? Here, we mean both physical meetings, as well as group chats through Messenger, Zoom, and so on.

[insert course 1]
[insert course 2]
[insert course 3]

10. On a scale from 1 to 5, where 1 is almost never, and 5 is daily, how often did you study together with your classmates when studying the following courses? Now, we mean physical meetings only.

[insert course 1]
[insert course 2]
[insert course 3]

11. On a scale from 1 to 5, where 1 is not worried at all, and 5 is very worried, how worried were you about contracting COVID-19?

During September–October.
During November–December.

[23] Since M students took the course in supply chain management in the second half of the semester, this changes to November–December M students.

[24] This differs between programs as follows:

EM: Complex Analysis, Mathematical Statistics, Microeconomic Theory

EP: Complex Analysis, Dynamics, Statistical Thermodynamics

I: Mathematical Statistics, Microeconomic Theory, Supply Chain Management

M: Mechanics, Supply Chain Management, Thermodynamics and Fluid Mechanics

12. On a scale from 1 to 5, where 1 is not negatively at all, and 5 is very negatively, how was your mental health affected by the pandemic? Here, we refer to the lack of social contacts, fewer in-person lectures, boredom, and so on.

During September–October.
During November–December.

13. On a scale from 1 to 5, where 1 is not motivated at all, and 5 is extremely motivated, how motivated were you in your studies last semester, generally speaking?

During September–October.
During November–December.

14. On a scale from 1 to 5, where 1 is very dissatisfied, and 5 is very satisfied, how satisfied were you with the quality of your life last semester? Here, we mean well-being broadly speaking, joy of life, view of the future, and so on.

During September–October.
During November–December.

15. Same question as above, only referring to the period immediately before the onset of the pandemic (February/March 2020).

16. Immediately before the pandemic, how active were you in student life? Here, 1 means not active at all, and 5 means very active.

17. What is your view on the restrictions imposed in Sweden in response to the spread of the virus?

- [ ] Well-balanced[25]
- [ ] Too harsh.
- [ ] Too lenient.

18. A question regarding people you know (friends and acquaintances). On a scale from 1 to 5, how many of them know each other? Here, 1 means that none of my friends and acquaintances know each other, and 5 means that almost all of my friends and acquaintances know each other.

[25] The Swedish adverb used here, *lagom*, has no one-word translation into English. Other suggestions include ”about right”, or ”just enough”.

19. How large a share (in %) of your classmates are in each of the following categories? It should sum to 100.

They are my close friends, and we can talk about anything!

They are my friends, but I do not know them well enough to talk about deeper stuff.

I know them, and maybe talk to them when I meet them, but I would never use social media to communicate with them.

I do not know them, and I never communicate with them.

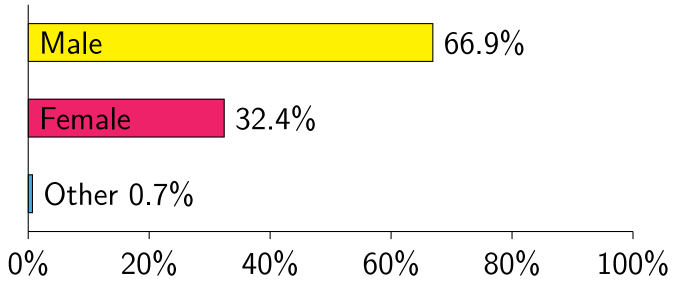
20. On a scale from 1 to 5, where 1 is not popular at all, and 5 is extremely popular, how do you think your classmates view you?

21. Write down the initials of your five closest classmates.[26]

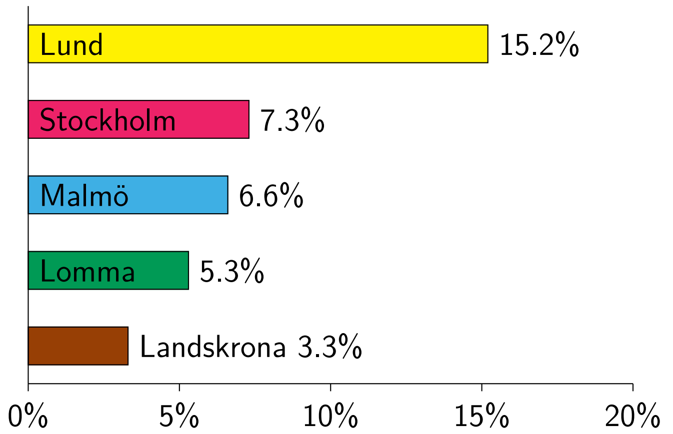
[26]We drop this question for the non-treated students.

D. Survey Results

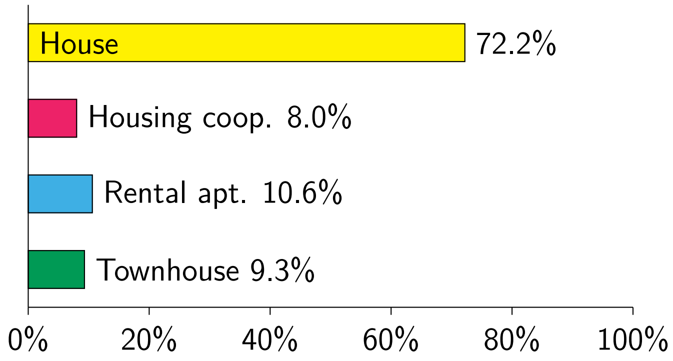
1. What is your gender?



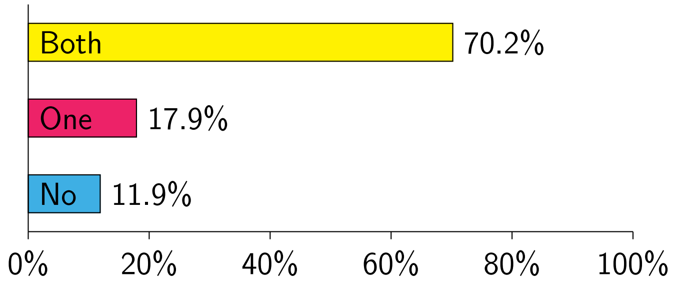
2. In which municipality did you live at the time of your graduation from high school?
   Five most prevalent municipalities:



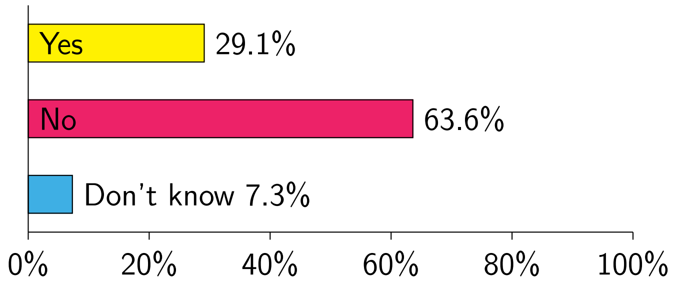
3. When growing up, in what type of dwelling did you mainly live?



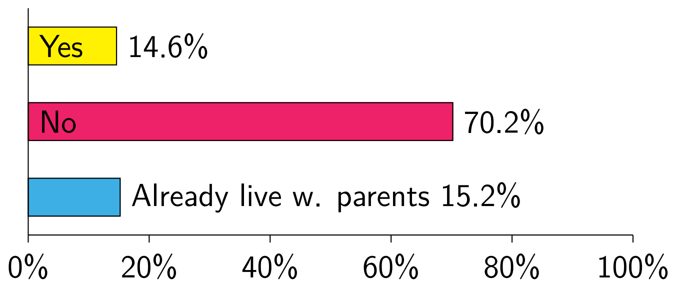
4. Does anyone of your parents have a college or university degree?



5. Has anyone of your parents been the CEO or a board member of a publicly listed company?

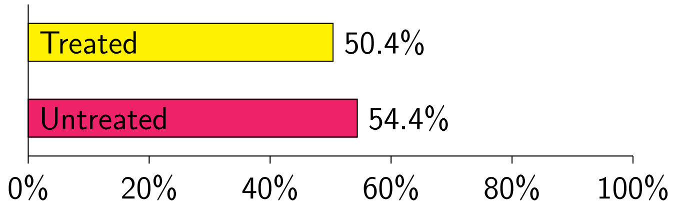


6. Much of last semester was online. Did you at any point during the semester move back to live with your parents because of this?

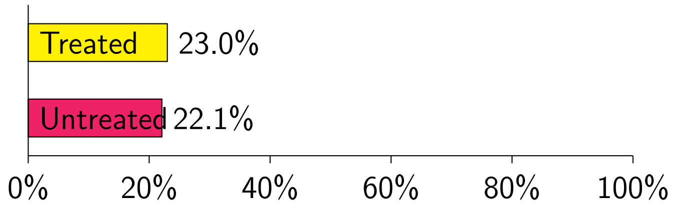


7. During the period September–October last semester, how large a share (in %) of your total time spent studying, did you spend on each of the following courses? By "time spent studying", we mean the sum of lectures, exercise sessions, self-study, exam cramming, and so on. It should sum to 100.

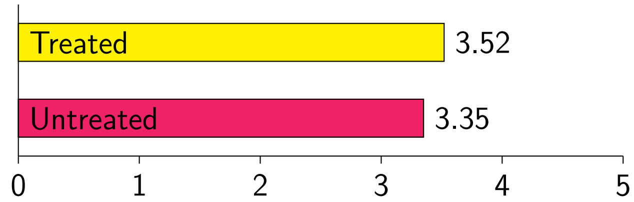
Complex Analysis:



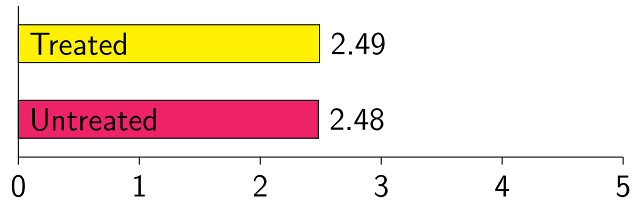
Supply Chain Management:



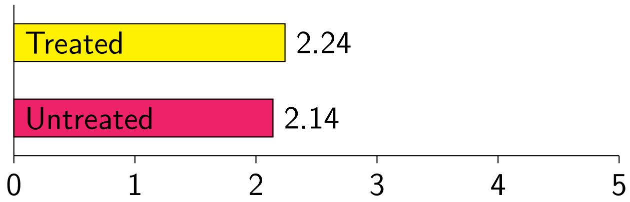
8. On a scale from 1 to 5, where 1 is very uninteresting, and 5 is super-interesting, how would you rate each of the following courses? *Note.* The table averages over all three courses weighted by ECTS credits, for treated and untreated students.



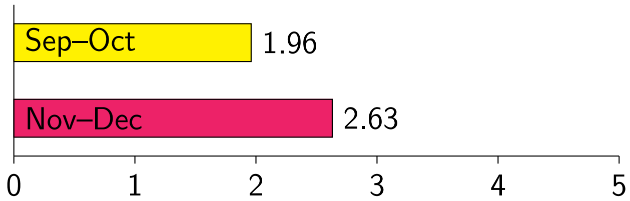
9. On a scale from 1 to 5, where 1 is almost never, and 5 is daily, how often did you study together with your classmates when studying the following courses? Here, we mean both physical meetings, as well as group chats through Messenger, Zoom, and so on. *Note.* Only the results for the spillover courses (Complex Analysis and Supply Chain Management) are presented.



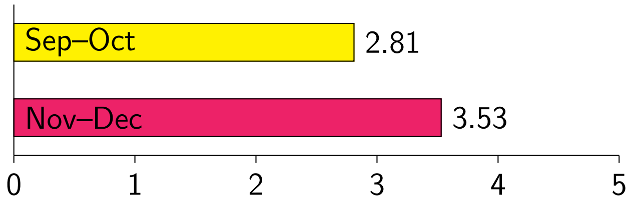
10. On a scale from 1 to 5, where 1 is almost never, and 5 is daily, how often did you study together with your classmates when studying the following courses? Now, we mean physical meetings only. *Note.* Only the spillover courses (Complex Analysis and Supply Chain Management) are presented.



11. On a scale from 1 to 5, where 1 is not worried at all, and 5 is very worried, how worried were you about contracting COVID-19?



12. On a scale from 1 to 5, where 1 is not negatively at all, and 5 is very negatively, how was your mental health affected by the pandemic? Here, we refer to the lack of social contacts, fewer in-person lectures, boredom, and so on.



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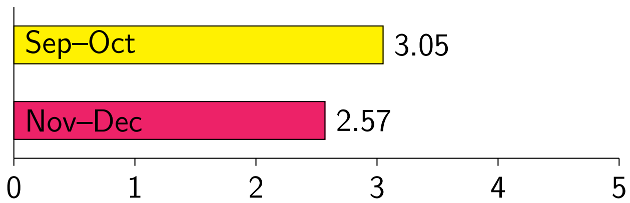

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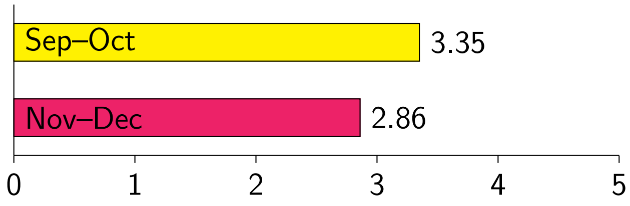

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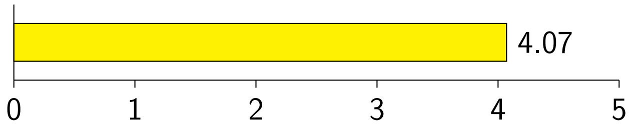
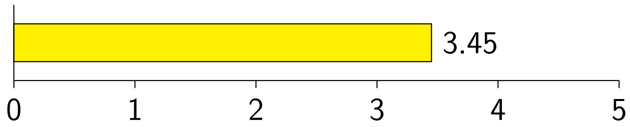
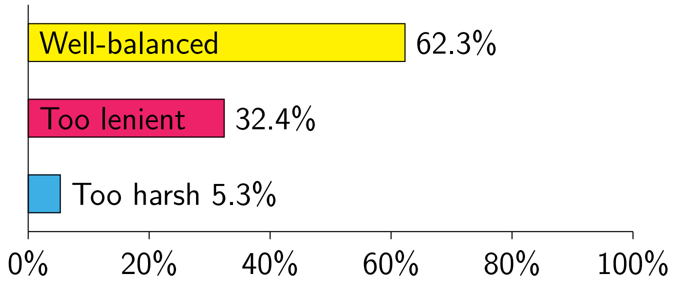


16. Immediately before the pandemic, how active were you in student life? Here, 1 means not active at all, and 5 means very active.



17. What is your view on the restrictions imposed in Sweden in response to the spread of the virus?



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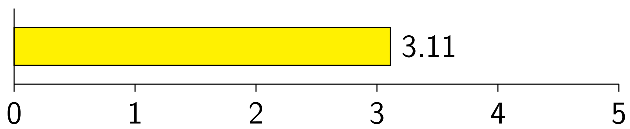
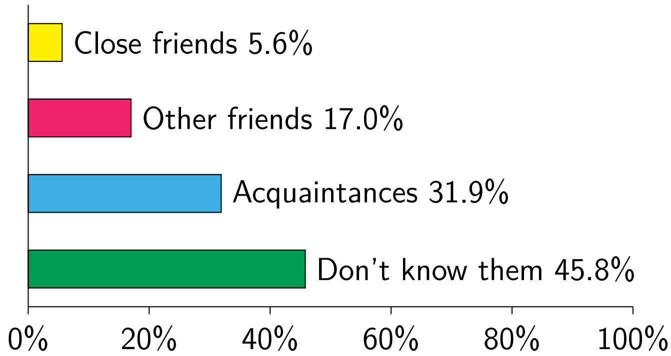


19. How large a share (in %) of your classmates are in each of the following categories? It should sum to 100.



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