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Academic performance and selective admission policies

The impact of weighted SweSAT admission on academic performance in engineering programmes in Sweden

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Abstract

During the enrolment year of 2019 and 2020, some Swedish universities were presented with the opportunity to participate in an admission policy trial. The universities could choose to weigh SweSAT scores based programme specific requisites. The paper examines the policy implementation of weighted SweSAT admission in engineering programmes at Swedish universities. The question explored in the paper is whether academic performance, in terms of pass rates, increased as an effect of the policy or not. A difference-in-differences design is applied to investigate the causal effect of the policy implementation. The model primarily consists of two parts, accounting for university-specific effects and time-varying effects. As a robustness check, a time-varying control variable is integrated. The results suggest a negative causal effect of treatment. However, the findings are without substance and are likely better explained by omitted time-varying school-specific covariates not captured by the model. Thus, we encourage future research to extend the model, utilising more time-varying school-specific covariates to depict the actual treatment effect fully.

Keywords: Admission policy change, difference-in-differences, engineering programmes, SweSAT.

Contents

Abbreviations & Terminology

Abbreviations

- **ATET** - Average Treatment Effect on the Treated
- **DiD** - Difference-in-differences
- **SCHE** - Swedish Council for Higher Education
- **SHEA** - Swedish Higher Education Authority
- **STEM** - Science, Technology, Engineering, and Mathematics
- **SweSAT** - Swedish Scholastic Aptitude Test (SweSAT)
- **SweSATQ [SweSATV]** - Weighted SweSAT, emphasising quantitative [verbal] qualities

School-specific abbreviations

- **BTH** - Blekinge Institute of Technology
- **KTH** - Royal Institute of Technology
- **LTH** - Faculty of Engineering, Lund University
- **LTU** - Luleå University of Technology

Terminology

- **Academic performance** - A measure of completed ECTS by registered students withing one year of registration (in percent)
- **Counterfactual** - The outcome of a treated individual had it not been treated
- **Treated / [Treatment]** - Individuals exposed to / [the implemented policy]

1 Introduction

With an average study length of six years, Sweden has the highest average age of tertiary graduates (30.5) in Europe when entering the labour market. However, only 25% of the graduates obtain a degree that requires five years or longer to complete (Confederation of Swedish Enterprise, 2018). According to Swedish Higher Education Authority (2017), 20% of students drop out of programmes within the first year, explained by poor matches and poor student results in the first two semesters. The study also shows a negative relationship between drop-out rates and upper secondary school grades. I.e., students with better prerequisites dropped out to a lower extent. Naturally, the inefficiency caused by extended study duration is associated with a cost. Government expenditures on tertiary education amounted to 30.3 [2.9] billion SEK [Euro], which is equivalent to 101 [9.8] thousand SEK [Euro] per student or 0.6% of Sweden's GDP in 2018 (Statistics Sweden, 2019). According to the Confederation of Swedish Enterprise (2018), a two-year reduction in study duration for graduates of bachelor's programmes could impose a 52 billion SEK increase in GDP. It is not only the financial side of the economy that suffers from the inefficiency. Forecasts indicate a significant lack of engineers by the year 2035. Particularly affected engineering fields are physics, electrical engineering, and computer science. Given the high drop-out rate in engineering programmes (see Figure 7 and 8 in the Appendix) and increased demand, the number of admitted students would have to increase by 82 per cent to meet the forecast demand for engineers in these programmes. In addition, biotechnology and chemical engineering programmes would have to increase by 52 per cent to meet forecast demands (Swedish Higher Education Authority, 2021b). The high drop-out rate and forecast demand raise the question of whether the admission system could be improved such that applicants with more desirable characteristics are admitted.

Ultimately, minimising the drop-out rates at universities is vital to increase efficiency in human capital allocation. In the US., students apply to college using their Grade Point Average (GPA) score, a course-performance-based scale that ranges from 0 to 4. On this scale, a score of 4 corresponds to a grade of A or A^+. Anything below a D corresponds to a 0 in the scoring. The usual GPA score is calculated by taking the average of all high school grades. The GPA is the most crucial basis for admission. However, this unweighted method does not consider that some classes are more advanced than others[1]. Most ivy league schools in the US prefer to evaluate weighted GPA scores when reviewing applicants for admission, which arguably, represents a more just depiction of student performance (Crimson Education, 2021). This way, universities might increase suitable matching when deciding on admittance. In other words, students that perform better in later years in high school might be more desirable to admit since they display comprehension of more advanced subjects. Improving matching techniques is essential for any university. More qualitative matches may allow for a reduced share of drop-outs and may increase the share of degree attainment. Additionally, this is resource-saving in, for instance, human capital. It begs whether universities can improve admission selection by extending matching methods further. One way of extending the framework of admittance could be to weigh subject relevancy higher. Arguably, enrolling in a mathematics programme at a university should primarily be based on students' capabilities in mathematics. Likewise, a student of Law might be expected to have high verbal competencies compared to an econometric student. Potentially, universities that introduce a selection method in which programme-specific qualities are particularly judged might find more suitable counterparts. Consequently, admitted students should have greater programme-specific qualifications on average. I.e., the estimated effect is students who got admitted via SweSATQ who would otherwise not have been admitted via the unweighted SweSAT. In the end, the success rate of students could therefore improve. This way of student admittance is precisely what some Swedish universities participated in during the enrolment year of 2019 and 2020. To increase SweSAT's possibility to predict academic performance, the Swedish Council for Higher Education (SCHE) launched a trial admission policy where universities could choose to weigh SweSAT scores based on programme specific requisites—quantitative or verbal (Swedish Council of Higher Education, 2020b).

In the paper, the admission policy change is evaluated to shed some light on the following research question: *Did academic performance increase in treated engineering programmes by the implementation of weighted SweSAT admission?*

The remainder of the paper is organised as follows. Section 2 introduces the reader to the Swedish tertiary education admission system. Section 3 is divided into two parts: (i) relevant economet-

[1] For example, English AP (Advanced Placement) is consider tougher than "regular" English.

ric theory to provide the reader with a sizeable econometric toolbox to understand the method of choice, and (ii) previous literature using either the same methodology or examining a related research question. Section 4 consists of the papers' delimitations, an overview of the data, and the method of choice. In section 5, the results are presented, analysed and discussed. Lastly, Section 6 concludes the paper.

2 Background

2.1 The Swedish admission system

A requirement for higher education at Swedish universities is, first and foremost, that a student has graduated from upper secondary school. Further, programme-specific prerequisites require a student to have studied particular courses at upper secondary school. For instance, to be eligible for engineering programmes, students need to have passed at least mathematics 4. Students can apply to higher education utilising two different paths. First, students can apply using GPA scores of courses partaken at upper secondary school. The second application possibility requires taking the Swedish Scholastic Aptitude Test (SweSAT). The test is not a requirement, but since applicants can utilise both methods simultaneously, taking it might increase acceptance odds. Taking the SweSAT puts the applicant in two different application groups, one group for upper secondary school GPA scores and another for SweSAT scores. The university can choose what ratio to use between upper secondary school GPA, and SweSAT (however, no less than 1/3 in either group) of the available places offered (Swedish Council of Higher Education, 2021).

The SweSAT consists of two sections. On the one hand, students are tested on their quantitative capabilities. In particular, the quantitative section consists of four parts: quantitative reasoning, mathematical problem solving, quantitative comparisons, diagrams, tables and maps. On the other hand, students are tested for verbal qualities, e.g., Swedish vocabulary, Swedish sentence completion, and reading comprehension in English and Swedish. All questions are multiple-choice. The SweSAT score is currently valid for eight years, contrary to the upper secondary school GPA, which has no expiration date. Prior to 2020, the SweSAT score was valid for five years. However, as a consequence of the COVID-19 pandemic, the government decided to extend the time to avoid some results from getting voided (Swedish Council of Higher Education, 2021; Government Offices of Sweden, 2020).

In 2019, the SCHE presented some universities with the option of weighing test results from the SweSAT. Universities had the option of weighing the two types of qualities examined in SweSAT. Universities weighed the two parts based on relevancy to the programme. For example, engineering universities weighed the quantitative section higher than the verbal section. Further, some social science programmes weighed the verbal section higher. As shown in 2.3, 11 universities participated in this proposal, affecting students that applied in the fall of 2019 and 2020 (Swedish Council of Higher Education, 2020a).

2.2 COVID-19

COVID-19 struck in early 2020, shortly after the policy implementation, and the World Health Organisation declared it a worldwide pandemic on March 11 (World Health Organization, 2020). The pandemic raised a significant concern and eventually induced the world into an economic recession, ongoing to this day. Various restrictive actions were taken to combat the outbreak. In Sweden, the Pubic Health Agency of Sweden recommended that all on-campus lectures and examinations were to seize to be conducted and instead transition to digital platforms regarding lectures as well as examinations (Public Health Agency of Sweden, 2020).

Although we do not yet know the long-term financial impact of the ongoing pandemic, its' short-term negative impact has been substantial and apparent. For instance, the OMXS30 fell 28% February 21 to March 20 (Nasdaq, 2022). During financial uncertainty, the number of individuals applying to higher education has proven to increase (Swedish Higher Education Authority, 2022; Swedish Council for Higher Education, 2021). However, the increase consists of an over-representation of particular groups—specifically, young students descending from households with high parental education, which is a group that already was over-represented at universities (Swedish Higher Education Authority, 2021a). The effect on academic performance is, however, not yet clear-cut. There exists limited research on the impact of COVID-19 on academic performance and even less on academic performance in higher education. According to the Swedish Higher Education Authority, the immediate effect of COVID-19 on academic performance[2] was minor. In engineering programmes, the immediate academic performance increased by 1pp (from 75% to 76%) between spring 2019 and spring 2020. In addition, their study found no statistically significant change in student drop-out rates. The change in academic performance and the seemingly unaffected drop-out rates could be seen as surprising, considering the drastic change resulting from COVID-19 restrictions. However, it is essential to remember that the measures of performance do

[2]Immediate academic performance, in the context of their study, is a measure of ECTS completed the same semester in which the student registered on the course.

not fully depict the causal effect of COVID-19 on academic performance (Swedish Higher Education Authority, 2022). We stress that their study is merely a presentation of statistics given the specific time frame, and inference is not addressed. For example, the slight increase in academic performance in engineering programmes could result from altered student composition rather than a causal effect of COVID-19 and the changing academic arena.

The existing literature has mainly focused on mental health and discussed its' linkage to academic performance. The physical closure of schools, colleges, and universities has increased mental health issues. In China, for instance, 25% of students reported that they experienced an increased level of anxiety as a result of COVID-19 (Cao et al., 2020). Mudenda et al. (2020) argues that the rising anxiety levels, and increase in mental health issues in general, eventually will affect academic performance negatively. However, as previously mentioned, the short-term impact on academic performance has not yet had the time to be empirically and thoroughly evaluated.

2.3 Treated programmes at each respective university

Chalmers University of Technology
Bachelor of Science in Engineering
Degree of Master of Science in Engineering
Karlstad University
Degree of Master of Laws
Study Programme for Human Resource Management
Linköping University
Degree of Bachelor of Arts in Pre-School Education
Luleå University of Technology
Degree of Master of Science in Engineering
Lund University
Degree of Master of Science in Engineering
Mid Sweden University
Degree of Bachelor of Science in Nursing
Malmö University
Degree of Master of Science in Dental Surgery
Stockholm University
Bachelor of Science in Social Work
Umeå University
Bachelor of Science in Engineering
Degree of Master of Science in Engineering
University of Gothenburg
Bachelor of Science in Social Work
Uppsala University
Degree of Master of Science in Engineering

3 Related works and theory

This section commences by reviewing previous research on educational economics and academic performance using difference-in-differences (DiD) estimation. The section continues with the econometric foundation leading up to the adopted approach introduced in section 4.

3.1 Previous literature

As previously mentioned, the demand for engineers is high, and some engineering profiles are at the risk of being in major shortage in the future. For instance, the number of admitted students in electrical engineering and computer science & engineering needs to double to meet 2035 projected demand (Swedish Higher Education Authority, 2021b). Of the admitted engineering students in Sweden, only 52% completed their degree within the set time frame of 10 semesters. Further, the completion rate amounted to 66% after 12 semesters (equivalent to six years), and of the remaining 34%, a vast majority (95%) had more than 30 ECTS remaining to complete their degree (Swedish Higher Education Authority, 2019). The statistics are alarming, and the insufficient projected supply of engineers can be addressed in several ways. One way of increasing the number of engineers is to increase the number of spots at different engineering programmes and offer more engineering profiles at more universities. However, this paper's focal point is on academic attainment, i.e., how universities can improve matching techniques to increase retention and graduation rates.

Astin et al. (1997) found that academic performance is highly correlated with student retention, similarly to Allen et al. (2008) who found that first-year academic performance is critical with regards to student retention—underscoring the importance of sufficient student preparation prior to university. Thus, academic performance might be a key element regarding the academic attainment of engineering programmes. Finding a valid instrument to what drives academic performance could be the key to a successful admission policy. Ting and Man (2001) attempt to predict the first-year academic performance of engineering students by regressing SAT scores and psychosocial variables on GPA. The authors found that a student with a high SAT score (mathematics or total score) had greater academic success in the first year. Felder et al. (1993) found a strong correlation between SAT scores and academic performance for the introductory courses in chemical engineering at North Carolina State University. Unfortunately, both studies may be of limited value as the models used likely suffer from omitted variable bias (OVB). There exist many plausible explanatory variables which may affect the GPA of engineering students. For instance, Wikström and Wikström (2017) find evidence of parental education and family income—to name a few—to be such explanatory variables, which are not accounted for in the framework of Ting and Man (2001). Thus, when predicting academic performance, the empirical design should account for explanatory observables, such as family income, and unobservables, such as student ability. In contrast to Ting and Man (2001), De Winter and Dodou (2011) use factor analysis combined with a step-wise linear regression in an attempt to predict academic performance. Although the authors find some interesting correlations, the question of inference is of greater importance when evaluating a policy implementation. In both Ting and Man (2001) and De Winter and Dodou (2011) any claim regarding causality cannot be made, and in the setting of policy evaluation, this is a necessity. Hence, in efforts to predict academic performance, linear regression models might not be well-suited.

Given that an adequate control group can be found for the treatment group, Chaudhary (2009) argues that a DiD strategy, instead, is particularly appropriate when evaluating the impact of policy implementations. In the case of Chaudhary (2009), the author deployed a DiD strategy to evaluate the impact of the school finance reform, *Proposal A*[3], and isolated the changes in expenditures caused by the policy change. Additionally, Francesconi et al. (2011) also use a DiD strategy when evaluating an educational policy, namely, an admission selection policy (based on admission tests); to investigate whether a more selective admission policy leads to an improved academic performance or not. More specifically, if the policy increased (i) the likelihood of completing the degree, (ii) the number of students obtaining top marks, and (iii) the number of students finishing their degrees within the set time. The DiD in Francesconi et al. (2011) utilises time variation in the interruption of selectivity schemes across departments within the same institution. I.e., the control and treatment groups are from the same institution and should, according to their study, be compatible for comparison and identification of parallel trends. The linear trend assumption is, later formally explained, the key identifying assumption in a DiD setup. The assumption can be challenging to fulfil, and an attractive option would be to condition the assumption on additional covariates. Caetano et al. (2022) show that two-way fixed effect (TWFE) estimations are generally not robust when

[3] *Proposal A* is a tax reform in Michigan, the US., which aimed to increase school expenditures in poorer districts by flooring per-pupil revenues across all districts.

conditioning on time-varying covariates. However, the authors suggest some regression alterations resulting in robust estimates. They achieved more robust estimates by allowing the time effect to be a function of group-specific covariates and time-varying group-specific covariates.

On the topic of fairness, several Ivy League schools have utilised weighted GPA admission for quite some time. One has to wonder, who benefits from such an admission policy? In the context of Sweden, Wikström and Wikström (2017) points out that males obtain better SweSAT scores, while females tend to obtain higher GPAs from upper secondary school. More specifically, their study showed that males' SweSAT was overall 1.3 points while females' GPA was 1 point higher than males. The gender difference was even more palpable in specific sub-fields, as males obtained a relatively higher score than females on the quantitative part of the SweSAT (2 points). Naturally, a weighted SweSAT admission policy would favour males in a setting where the programmes using SweSATQ are already over-represented by males. So, answering whether weighted SweSAT admission improves academic performance is highly relevant. It could potentially contribute to an increased gender inequality based on the invalid belief that the weighted SweSAT increases academic performance. In addition, the long-term effects could be harmful of having weighted admissions. For one, children would have to, at an even earlier age, have to commit to specific subjects to stay competitive. Studies by Lyrén (2008); Wolming and Wikström (2010) have also shown that GPA is a better predictor than SweSAT for academic performance, meaning that the long-term effect of a weighted SweSAT might lead to a decrease in academic performance as a consequence of neglected subjects.

There is no consensus in the literature about education on how to best estimate academic performance. However, in the setting of policy evaluation, the previous literature leans in favour of DiD simply due to its' practical design, allowing one to account for large numbers of omitted covariates (observed and unobserved). The upcoming section deep-dives into the econometrics and introduces the necessary assumptions of the chosen theoretical framework.

3.2 The econometrics

As previously discussed, causal inference is one, if not the main, objective when evaluating any policy implementation. More specifically, controlling for unobserved factors which may have affected the outcome. Causal inference is crucial for the research question of this paper as corona struck shortly after the implementation of weighted SweSAT admission, drastically altering how universities lectured and tested students. To clarify, students partook in the education and examination from the comfort of their homes instead of on campus. Experiments, instrument variables (IV) or regression discontinuity (RD) methods are often preferred to estimate causal effects. However, in applied work, good instruments and exploitable discontinuities are scarce. Thus, researchers are often limited to alternate methods, e.g. fixed-effect and DiD estimation (which is an extension of the fixed-effect model using aggregate data), to control for unobserved-but-fixed omitted variables (Angrist and Pischke, 2008).

3.2.1 Fixed-effect estimation

Panel data can be analysed by running a pooled OLS, treating all observations as independent such as:

$$Y_{it} = \alpha + X_{it}\beta + \varepsilon_{it} \quad \text{where} \quad i = 1,...,N \quad \text{and} \quad t = 1,...,T \tag{1}$$

However, to acquire unbiased and consistent estimates of the parameters, the *zero conditional mean assumption*, $E[\varepsilon_{it}|X_{i1},...,X_{iT}] = 0 \implies Cov(\varepsilon_{it}, X_{iT}) = 0$, must hold Angrist and Krueger (1999); Angrist and Pischke (2008). This assumption can, for one, be violated if there exists an omitted variable which is correlated with the included regressors, as in the case of Ting and Man (2001). Angrist and Krueger (1999) emphasise this as one of the pitfalls in regression analysis, i.e., there may be additional covariates that are not accounted for, which may affect the estimates further.

To avoid making mistakes about causal inference; suppose we instead construct a simple linear panel data model where the variable of interest, academic performance (Y_{it}), is a function of a vector of exogenous regressors (X_{it})

$$Y_{it} = \alpha + X_{it}\beta + v_{it} \quad \text{where} \quad v_{it} = \varepsilon_{it} + \eta_i \tag{2}$$

thus splitting the error term where η_i is an individual specific error term which does not change over time, e.g. genetics. Meaning that one now has a two-part additive error term, one of which is time-invariant (η_i) and another which is not (ε_{it}). With a two-part error term, one can utilise the fixed-effects model's property of eliminating bias by having repeated observations over different time periods, i.e., the *within estimation* (Angrist and Pischke, 2008). These η_i could be accounted for by including a unique dummy for each i, but with a large data set it may appear daunting to run i many estimations. However, just as Angrist and Pischke (2008) points out, it is algebraically equivalent to treat the estimated individual parameters as estimations in deviations from means. Thus, rewriting Eq (2) in terms of means:

$$\overline{Y}_i = \alpha + \overline{X}_i\beta + \overline{\varepsilon}_i + \overline{\eta}_i \tag{3}$$

where

$$\overline{Y}_i = \frac{1}{T}\sum_1^T Y_{it}, \qquad \overline{X}_i = \frac{1}{T}\sum_1^T X_{it}, \qquad \overline{\varepsilon}_i = \frac{1}{T}\sum_1^T \varepsilon_{it} \qquad \overline{\eta}_i = \frac{1}{T}\sum_1^T \eta_i$$

Next, subtracting Eq. (3) from Eq. (2) which leaves us with the deviation from the mean:

$$\overline{Y}_{it} - Y_{it} = \big(\alpha + X_{it}\beta + \varepsilon_{it} + \eta_i\big) - \big(\alpha + \overline{X}_i\beta + \overline{\varepsilon}_i + \overline{\eta}_i\big) \tag{4}$$

$$= (X_{it} - \overline{X}_i)\beta + (\varepsilon_{it} - \overline{\varepsilon}_i) \tag{5}$$

Lastly, OLS is applied to estimate β, i.e., the within estimator (Angrist and Pischke, 2008). The estimation of β is now implicitly controlling for omitted individual-specific variables, meaning that OVB is partly eliminated.

3.2.2 Difference-in-differences

The fixed-effect model can be extended to control for omitted time-varying variables. As revealed by the name, difference-in-differences is a two-step differencing process. First, estimating the *within difference*, previously derived from the fixed-effect model. Second, estimating the *first difference* (Angrist and Pischke, 2008). Consider a setup where the variable of interest, academic performance (Y_{ist}), is a function of school-specific effect (γ_s), time-specific effect (λ_t), the treatment effect (ρD_{st}), and an error-term (ε_{ist})

$$E[Y_{ist}|s,t,D_{st}] \iff Y_{ist} = \alpha + \gamma_s + \lambda_t + \rho D_{st} + \varepsilon_{ist} \tag{6}$$

where the link between the parameters can be described as follows (Angrist and Pischke, 2008):

$$\begin{aligned}
\alpha &= E[Y_{ist}|s = \text{untreated}, t = \text{pre}] = \gamma_{untreated} + \lambda_{pre} \\
\gamma &= E[Y_{ist}|s = \text{treated}, t = \text{pre}] - E[Y_{ist}|s = \text{untreated}, t = \text{pre}] = \gamma_{treated} - \gamma_{untreated} \\
\lambda &= E[Y_{ist}|s = \text{untreated}, t = \text{post}] - E[Y_{ist}|s = \text{untreated}, t = \text{pre}] = \lambda_{post} - \lambda_{pre} \\
\rho &= \big((E[Y_{ist}|s = \text{treated}, t = \text{post}] - E[Y_{ist}|s = \text{treated}, t = \text{pre}]) \\
&\quad - (E[Y_{ist}|s = \text{untreated}, t = \text{post}] - E[Y_{ist}|s = \text{untreated}), t = \text{pre}])\big) = \rho
\end{aligned}$$

The within difference eliminates any time-invariant school-specific effects. Suppose one engineering programme at one university is more difficult than the equivalent at another university. However, since the programmes have similar structure over time, the difficulty of each programme could reasonably be assumed to be constant over time. I.e., regardless of year, the courses within the programme, e.g. Calculus 1, are equally difficult. We commence by deriving the within difference for the treatment group and control group, respectively, by subtracting Eq. (6) from itself at different time-periods, t, as shown below:

Treatment Group

$$E[Y_{ist}|s = treated, t = post, D_{treated \cdot post} = 1] - E[Y_{ist}|s = treated, t = pre, D_{treated \cdot pre} = 0] =$$

$$(\cancel{\gamma_{treated}} + \lambda_{post} + \rho \underbrace{D_{treated \cdot post}}_{=1} + \varepsilon_{treated \cdot post}) - (\cancel{\gamma_{treated}} + \lambda_{pre} + \varepsilon_{treated \cdot pre}) = \tag{7}$$

where $E[\varepsilon_{ist}|s,t] = 0$

$$\lambda_{post} - \lambda_{pre} + \rho \tag{8}$$

Control Group

$$E[Y_{ist}|s = control, t = post, D_{control \cdot post} = 0] - E[Y_{ist}|s = control, t = pre, D_{control \cdot post} = 0] =$$

$$(\cancel{\gamma_{control}} + \lambda_{post} + \varepsilon_{control \cdot post}) - (\cancel{\gamma_{control}} + \lambda_{pre} + \varepsilon_{control \cdot pre}) =$$

$$\lambda_{post} - \lambda_{pre} \tag{9}$$

The beauty of a DiD design lies in versatility. The programme taught at one university does not have to be identical to the same programme taught at the other university, as any heterogeneity is eliminated by the within difference. The first difference eliminates the time-varying effect. The COVID-19 virus struck in early 2020, changing how both lectures are taught, and exams are constructed. The pandemic is an example of a time-effect which may have affected students admitted in 2019 (as lock-down began during the spring of 2020) (Public Health Agency of Sweden, 2020). However, this time-effect is assumed to have affected universities to the same degree since they obliged the government's decision of lock-down at the same time (from 18 March 2020). Thus, the change in academic performance due to COVID-19 (or any other time-effect) is eliminated by subtracting the control group from the treatment group. I.e., subtracting Eq. (9) from Eq. (8) leaves us with the average treatment effect on the treated (ATET).

$$(\lambda_{post} - \lambda_{pre} + \rho) - (\lambda_{post} - \lambda_{pre}) = \rho \tag{10}$$

However, two fundamental assumptions, in particular, have to be fulfilled to get unbiased estimates of the treatment parameter, ρ. First, the *strict exogeneity assumption*. Second, and often considered the main identifying assumption, the *parallel trend assumption*. The former assumption is associated with the within difference estimation and the latter with the first difference estimation, the two stages in DiD.

In order to acquire a more efficient estimate of the parameter ρ, the DiD model can be extended to include additional covariates (re-introducing the X_{it} vector). When extending the model, however, one would typically refrain from including covariates which themselves could be affected by the treatment, referred to in the literature as *bad controls* (Angrist and Pischke, 2008).

3.2.3 Strict exogeneity assumption

The strict exogeneity assumption, which is in alternate version of the *zero conditional mean assumption*, $E[\varepsilon|X] = 0$, states:

$$E[\varepsilon_{it}|X_{i1}, X_{i2}, ..., X_{iT}, \eta_i] = 0 \quad \text{where} \quad i = 1, ..., N \quad \text{and} \quad t = 1, ..., T \tag{11}$$

In contrast to the zero conditional mean assumption, equation (11) emphasises that the time-varying part of the error term, ε_{it} needs to be uncorrelated with the treatment indicator and all control variables for all periods (Angrist and Krueger, 1999). The condition is stricter than contemporaneous exogeneity, which only requires the error term to be uncorrelated with the explanatory variables for the same period. In the context of this paper, this assumption is reasonably easy to fulfil, as the vector of explanatory variables cannot contain lagged values of Y_{it}. In other words, the explanatory variable X_{it}—e.g. upper secondary school GPA—can not be dependant of Y_{it}—e.g. pass rates in university—which, by construction, can not occur since students can not re-do upper secondary school as it is a prerequisite for tertiary education.

3.2.4 The parallel trend assumption

In addition to the strict exogeneity assumption, the parallel trend assumption must hold. The parallel trend assumption states that in the absence of treatment, the difference between the *treatment* and *control* group is constant over time, i.e., exhibiting the same trend (Angrist and Pischke, 2008). Loosely speaking, the treatment and control group should be presented as a set of two parallel lines in a graph. However, they are not restricted to only being linear, as shown by Sommers et al. (2015). They can, in fact, follow a higher-order function; as to why many authors (e.g. Angrist and Pischke (2008), (Lechner et al., 2011) and Wing et al. (2018)) instead refer to it as the *common trend assumption*. Lechner et al. (2011) mathematically formalise the common trend assumption as follows:

$$E[Y_1^0|X=x,D=1]-E[Y_0^0|X=x,D=0]= \tag{12}$$

$$E[Y_0^0|X=x,D=1]-E[Y_0^0|X=x,D=0]= \tag{13}$$

$$E[Y_1^0|X=x,D=1]-E[Y_0^0|X=x,D=0]; \quad \forall x \in X \tag{14}$$

If the parallel trend assumption holds, then one can account for any unobserved explanatory variables in the X_{it} vector. The idea is simple; given that the control and treatment groups exhibit the same pattern, the covariates that determine Y_{it} should be the same. Thus, the parallel trend assumption implicitly accounts for these unobserved covariates. The parallel trend assumption, complemented with theoretical rationale and conceptual reasoning, is the motivation as to why the control group is a valid counterfactual in the DiD framework (Angrist and Pischke, 2008). We can not understate the importance of the parallel trend assumption as, without it, estimates can be neither unbiased nor consistent. I.e., of no value.

3.2.5 Control variables in DiD

As mentioned in 3.2.2, one can include control variables to DiD models. In the context of this paper, time-varying school-specific effects, e.g. grades, might have changed at a national level over the years; however, they may also change on a school-specific level due to some reason. Since upper secondary school grades are a confounding variable[4], then we might want to account for this when analysing the ATET by regressing with upper secondary school GPA admittance as a control variable as a proxy for proficiency-level of students. The model could then be specified as follows:

$$Y_{ist}=\alpha+\gamma_s+\lambda_t+\rho D_{st}+\beta X_{st}+\varepsilon_{ist} \tag{15}$$

[4]Meaning, highly correlated with both the outcome variable as well as the treatment.

where X_{st} is the control variable(s). This vector (X_{st}) of covariates could include a lot more, for instance, the mean age of enrolled students during one cohort in a programme. If one can control for factors that differ between treatment groups that cause time trends in outcomes, one can also isolate and estimate the true treatment effect. In other words, including X_{st} might reduce bias. However, the criterion is that X_{st} has to be exogenous, i.e., unaffected by treatment. An endogenous control variable would lead to biased estimates of the treatment parameter, ρ (Fredriksson and Oliveira, 2019).

Control variables at the individual level (Z_{ist}) could also be included. However, this is not a necessity to get unbiased estimates but will lead to a reduced standard error, thus, higher precision when estimating the treatment effect (Angrist and Pischke, 2008; Fredriksson and Oliveira, 2019)

4 Data and methodology

Section 4, Data and methodology, commences by introducing the delimitations. Then outlines, motivates and presents the choice of data and thoroughly describes the data management process. The section concludes by presenting and motivating the adopted approach.

4.1 Delimitation

Due to the design of the paper, data is collected for *untreated* and *treated* programmes at universities in order to allow for analysis of the effect of weighted SweSAT scores. 11 universities participated in weighing the application through SweSAT (Swedish Council of Higher Education, 2020a). Untreated programmes' are compared with treated programmes. In Table 1, universities applicable to the study that participated in the SweSAT weighted admission trial are shown. Untreated universities with compatible programmes are included in the study (see Table 6 for programme specification).

Table 1: SweSAT weighing matrix for universities that participated in the SweSATQ/SweSATV application process (Swedish Council of Higher Education, 2022)

	Fall 2019	Spring 2020	Fall 2020	Spring 2021	Fall 2021
A. Engineering Programmes					
Chalmers University of Technology	75/25	-	75/25	-	-
Luleå University	75/25	-	75/25	-	-
Lund University	75/25	-	75/25	-	-
Umeå University	75/25	-	75/25	-	-
Uppsala University	75/25	-	75/25	-	-
B. Social Science Programmes					
Karlstad University	-	-	40/60	-	
Stockholm University	-	25/75	25/75	-	-
University of Gothenburg	-	40/60	40/60	40/60	-

As a strategic necessity, some universities that used SweSATQ/SweSATV are not included in the study. Further, some besought control universities have been excluded due to inaccessibility. The first rationale for delimitation is that the characteristics measured by SweSATQ/SweSATV (quantitative/verbal) need to be presumed to affect student performance in a specific manner. For example, Malmö University's dental practitioner training program is within the treatment group, i.e. incorporated weighted SweSAT scores in admissions, but is excluded from the analysis since the connection between greater quantitative or verbal skills and dentistry is not clear-cut. In other words, being better at one of the two should, presumably, not affect a student's performance within dentistry[5]. Hence, the ideal programmes to evaluate are engineering programmes. Engineering programmes weighed the quantitative qualities higher in SweSAT results as the course curricula are heavily centred around mathematics, statistics and other quantitative focalised sciences.

Second, some universities' LADOK departments dismiss the request to participate in the study, making student performance data—student results—inaccessible. Swedish universities are obligated to share data of student results according to Swedish law since student grades are subject to the principle of openness but are allowed to charge an administration fee (OLS 2009:400). Since it is essential to compare performance over time across many programmes and courses, the cost is high if LADOK incites compensation. Further, some LADOK departments only send data via postal mail, making the compilation of data tedious and infeasible. Lastly, universities are excused from sharing data if it hinders the proper work conduct (in accordance with 6:4 OSL). Unfortunately, many universities are excluded from the sample due to these reasons, which prompts the paper with challenges. Some are omitted by choice, and some are involuntarily left out.

Third, to conduct the DiD analysis, treated programmes must be comparable to untreated programmes. This criterion regards engineering programmes as some universities offer more particular specialisations than others. Thus, the programmes examined are compatible for comparison across treatment groups. Hence, some more unique programmes are excluded from the analysis and the more typical programmes are analysed.

Last, the data need to be compatible for comparison across universities (more on this later in 4.2).

[5]The same line of reasoning explains why preschool teacher education and nursing education programmes are excluded from the sample.

Hence, the programmes that are the basis for analysis in this paper are shown in Table 6 in the Appendix.

4.2 Data & descriptive statistics

Data of student grades ($N = 260,825$) on 411 unique courses (see Table 9) is gathered in collaboration with universities' local LADOK support units. LADOK is a national student administration system, owned[6] and used by Swedish universities for various study administration processes, e.g. documenting student registration and grade administration (LADOK, 2022). In Sweden, technical and scientific programmes, such as engineering programmes, primarily use the *TH* grading scale when grading students. The scale consists of four grades: U—failed grade, 3—passing grade, 4—passing grade without praise, and 5—a passing grade with praise. However, the universities are free to choose their grading scale as they please, and variations occur. At some higher education institutions, the *AF* scale is used to grade students, which consists of seven grades: F—Insufficient, FX—-Insufficient (complement possible), E—Sufficient, D—Satisfactory, C—Good, B—Very good, and A—Excellent. These grades are used as proxies for student performance within courses in programmes in this paper. When examining passing rates, anything above a failed grade (e.g., U, F and FX) is deemed passing.

The data collection began with dialogues about student grade availability with each LADOK department to comprehend what type of data is accessible. Most LADOK departments have access to the desired student module grade, however, in various formats. The study demands student grades in each course over some time to observe any potential effects of SweSATQ. However, we were oblivious to what type of data LADOK has access to as the data is not publicly available. It was crucial to avoid mistakes when ordering the data (and that the demanded data was calculated, precise and motivated), as multiple requests could make LADOK more inclined to refer to 6:4 OSL.

Unfortunately, LADOK does not obtain records of students' grades who applied via SweSATQ. Naturally, the best way of testing the effect of weighted SweSAT would have been to observe the accomplishments of SweSATQ students in comparison to "ordinary" students. Further, the LADOK departments do not store data on student performance filtered by programmes. Instead, they store

[6]LADOK is also partly owned by the Swedish Board of Student Finance (CSN).

both aggregate and individual student performance data for each course held at the university. Hence, a comprehensive list of which course modules are included in each programme needed to be compiled in order for the LADOK departments to know what type of data should be extracted (see Table 9). The module specification list is established with the help of detailed education plans for each programme for each respective cohort. Reasonably, the effect of SweSATQ should be more apparent in the first year of studies at universities. By including exam results further than the first two semesters, the effect of students' high-school and SweSAT results on their academic performance should be minimal as the student would have had time to acclimate to the university studies. Engineering programmes only admit students to the fall semester each year. Pass rates of the first two semesters are consolidated to an aggregate pass rate for each enrolment year to obtain better matches across universities. The aggregate pass rate will improve course overlap across treatment and control groups. As the education plan changes year from year, and due to the need for historical data, it is essential to compile a chronicle list for each historical cohort within each solicited programme. The reason historical data is needed is to observe the trajectories in pass rates to support parallel trends. Hence, the data collected stretches over several years, before and after the treatment period. The data ranges from courses elapsed in the fall of 2015 to the spring of 2022. This should be sufficient to observe linear trends between programmes at different universities. However, several programmes were not offered across all schools prior to 2017. Thus, only data from fall 2017 and onward were used.

Evidently, to investigate the evolution of passing grades, a proxy of how many students failed a course is needed. LADOK departments do not keep a record of how many students fail a course. Thus, the passing rates are backwards inducted using the number of registered students in each course, combined with student results in each course. A cause for concern is that students at engineering programmes are allowed to attend a re-take exam in order to obtain a higher grade—so-called *plussning*—even though the student already passed the same exam previously. As this does not require the student to re-register to a course, including *plussning* would have riddled the pass rates with students re-taking the exam. The issue of *plussning* was solved by only extracting student grades of registered students at each course.

In summary, the data collected follows the format stated below:

- Aggregate (or individual) grades of students registered in a course module by the start date of the course module
  - For every course module within the first two semesters in all programmes in Table 9
  - For courses elapsed from the fall of 2015 to the spring of 2022 (latest available)
- Number of registered students in each course each enrolment year

With the data collected according to the format mentioned above, the pass rates are calculated by dividing the number of course-registered students with a passing grade (higher than fail) by the total number of registered students in that course. In addition, a weighted pass rate is calculated by factoring in the scale of the course, referred to as *academic performance*. Course modules have corresponding ECTS-credits (European Credit Transfer System) that can range between 1 to 30 points depending on the scope of the course. More comprehensive courses yield more ECTS-credits. Therefore, a weighted pass rate is advantageous to make courses comparable. The logic is that a passing grade in a more extensive course should be weighted more than a passing grade in a minor course to reflect student performance more justly. Thus, throughout the paper, academic performance refers to the per cent of completed ECTS by registered students within one year after registration[7].

In addition to the data on student performance, the lowest admitted upper secondary school GPA is gathered as a control variable for the change in the skill-level difference between universities. Specifically, the data is of students that apply through the so-called direct group (*BI*), i.e., applicants with completed upper secondary studies who provide eligibility without a supplementary grade. The data is collected from SCHE's admission statistics database for the admission years 2015 to 2021 Swedish Council for Higher Education (2022).

4.3 Estimating ATET

To estimate the causal effect of the weighted SweSAT policy implementation on the academic performance of engineering students, we follow the adopted approach of previous literature (see, for

[7]Note that this way of measuring pass rate will lead to a lower pass rate as some students pass courses in later academic years.

example, Chaudhary (2009); Francesconi et al. (2011)). The advantage of applying a DiD design is that it allows us to compare heterogeneous schools, as shown in Section 3.2.2. Also, the policy implementation overlapped with the COVID-19 pandemic, possibly imposing a significant time-specific effect. As discussed in Section 2, students from households with higher parental education drastically increased across all universities, implying that λ_t from Eq. (6) increased post-treatment. The LADOK departments do not record student characteristics such as parental background, and even if they did, information regarding which variables are important in predicting academic performance is imperfect. It might even be true that crucial characteristics are fundamentally unobservable and immeasurable. The DiD design allows us to account for these effects and is the primary reason it is an attractive option in the context of the SweSAT policy evaluation. Specifically, we define our DiD setup as follows:

$$E[Y_{ist}|s,t,D_{st}] \iff Y_{ist} = \alpha + \gamma_s + \lambda_t + \rho D_{st} + \varepsilon_{ist} \tag{16}$$

where α represents the initial pass rates, γ_s captures the school-specific effects, λ_t any time-specific effects, ρD_{st} is the treatment dummy, and ε_{ist} the error term. This model could be estimated using the sample means. However, we instead use regression tools in STATA[8] to derive the DiD estimates, which allow us to extend the analysis further by including additional regressors as well as capture the standard errors and interaction coefficients. Note that the *xtdidregress* used in the analysis accounts for heteroscedasticity and allows for clustering by using robust standard errors.

Before conducting any regressions, the parallel trend assumption is scrutinised as a violation of the assumption would invalidate the model as a whole. Thus, the analysis starts by optically investigating the parallel trends assumption for programmes across treated and untreated universities. Nine engineering programmes are evaluated (see Table 9). Several programmes are compared, 11 treated and 13 controls. The analysis starts with more general noteworthy results, followed by more detailed investigations. It is thought that programmes are similar in characteristics and therefore comparable across universities [9]. Many programmes are analysed since the consensus is that the linear trend will not hold in most cases. Programmes are exposed to time-varying school-specific

[8] The *xtdidregress* command in particular. Extensive information regarding *xtdidregress* can be found here.

[9] Similar in course content and thus comparable in terms of academic challenge.

factors, which could affect whether the parallel trend assumption holds. Still, if a linear trend can be identified, the effect of SweSATQ can be isolated and analysed. The argument that any potential pre-treatment collinearity is random is thought to be unlikely but is nonetheless scrutinised.

There is a worry that COVID-19 may have altered time-varying school-specific characteristics, affecting academic performance. To account for this, reduce bias and increase precision (reduced standard errors), we introduce a control variable for the lowest admitted high school GPA (*BI*) as *BI* could reflect changes in student composition. Additionally, studies have found high school GPA to be correlated with academic performance (see Wikström and Wikström (2017)). Thus, the new extended model is specified as follows:

$$E[Y_{ist}|s,t,D_{st},X_{ist}] \iff Y_{ist} = \alpha + \gamma_s + \lambda_t + \rho D_{st} + X'_{ist}\beta + \varepsilon_{ist} \tag{17}$$

where X_{st} is the vector (one-by-one in our model) with the control variables, *BI*. The reason is that even though the programmes are similar, the student demographic could vastly differ. Students admitted to Lund University have a higher *BI* than, for instance, students at Mid University, which should impose a greater academic performance on average. Initially, the idea was that student characteristics should have been eliminated in the within difference. However, the impact of the COVID-19 pandemic could have altered the student demographic—in particular, have altered the demographic *differently* across universities—as the competition to attend university increased.

It would be naive to think that controlling for *BI* would be a comprehensive control of changed student characteristics as a consequence of the COVID-19. Although, we argue that it is the most essential as it, to some extent, works as a proxy for characteristics such as *ambition* and *ability*. Nevertheless, as a robustness check, the analysis is complemented by running a separate DiD regression where the enrolment year 2020 is excluded.

5 Empirical analysis

The first step of the analysis is to identify any potential linear trends before the incursion of treatment. The segment is divided into several parts and begins by discussing breaches of the linear trend assumption by reviewing plots of observed means in academic performance of treated and untreated programmes. The analysis proceeds by visualising the programmes in which the parallel trend assumption is satisfied and further complemented by programmes where the parallel trend holds statistically (with and without control—*BI*). Conceptual arguments further motivating the parallel trend assumption are also presented. The section continues by analysing the average treatment effect on the treated (ATET) for the programmes that uphold the criterion for parallel trends. As a robustness check, alterations to the model are applied.

5.1 The parallel trend assumption

Examples of violations to the parallel trend assumption are presented below. Figure 1 and 2 show the mean outcome in pass rates over time for both the treatment group and control group. The dashed line indicates the control universities, and the data stretches from the fall of 2017 (HT17) to the fall of 2020 (HT20). The enrolled semester when treatment incurs for LTH and UU is the fall of 2019 and 2020, as seen in 1. However, since the passing rate data is aggregated for courses partaken during the first two semesters in each respective programme, the treatment takes place after the fall of 2018 (HT18) (indicated by the vertical bar). Hence, the linear trend assumption needs to be met for each time point before the vertical line in the coming figures. The pass rates of students in the engineering physics programme are shown in Figure 1 (treatment group—UU—and control group—KTH). Figure 2 shows the pass rates for students in the electrical engineering programme for the treatment group—LTH—and the control group—MIUN.

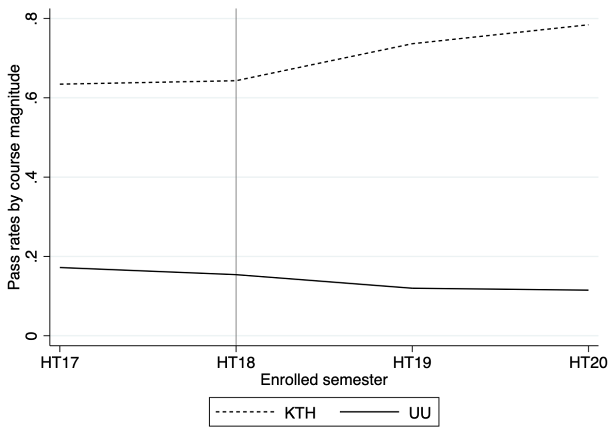

Figure 1: Pass rates in engineering physics

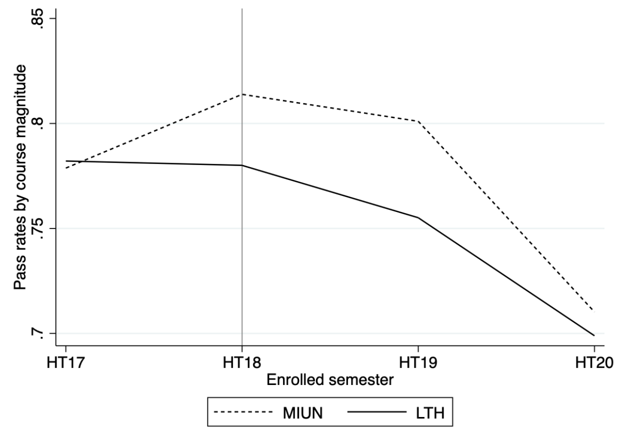

Figure 2: Pass rates in electrical engineering

The trends in Figure 1 are flat during the pre-treatment period, followed by a distinct increase in pass rates in KTH. In the treated university (UU), the pass rates continue with the same trend downwards. Yet, the effect of SweSATQ is not discernible in this case as the trends deviate from each other in the pre-treatment period, i.e., violating the parallel trend assumption. Further, Figure 2 is an example that represents most cases for the analysed programmes. Even though the programmes' contents might be similar, there are many other reasons why pre-treatment trends do not hold. One reason is that the programmes have arranged courses differently, during different periods, meaning that the programmes and the student components in the programmes do not match perfectly.

Table 2 validates the conclusion that the previously mentioned trends violate the linear trends criteria. Both examples have a p-value less than the 5% significance level. Hence, they are deemed impractical for further analysis.

Table 2: Linear trends test. H0: the linear trends are parallel during the pre-treatment period.

Programmes (Treated/Control)	F(1, 1)	Prob>F
Engineering physics (UU/KTH)	15339.98	0.0051
Electrical engineering (LTH/MIUN)	259.97	0.0394

Some programmes fulfil the parallel trend assumption when visually inspecting the pass rates. As shown in Figure 3, 4, 5, and 6, the parallel trends in the pre-treatment period are visually, somewhat, in accordance with the assumption. The trends follow the same general pattern during the pre-treatment years. Regardless, the magnitude of change between the years is different in the pre-treatment period in all examples. However, there is only a slight deviation in the trend of pass rates during the fall of 2018 in Figure 5. Typically, for the effect of weighted SweSAT to be comprehensible, the magnitude of change needs to be similar between the control and treatment groups. Otherwise, any alteration occurring post the treatment year (after 2018) can hardly be assigned to the change in SweSATQ admittance. As visually inspecting trends is quite the subjective mean of discerning the linear trends assumption, an F-test[10] for linear trends is run in Table 3.

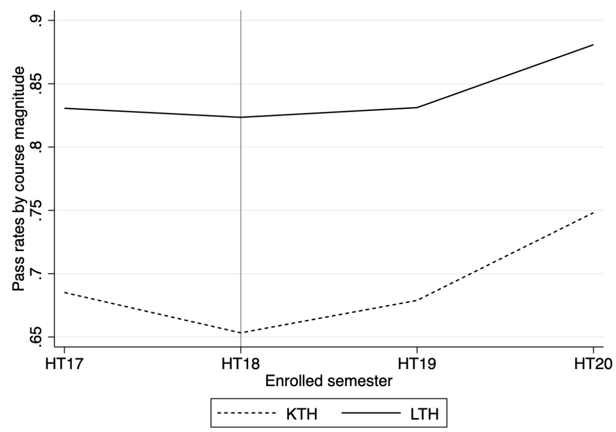

Figure 3: Pass rates in biotechnology

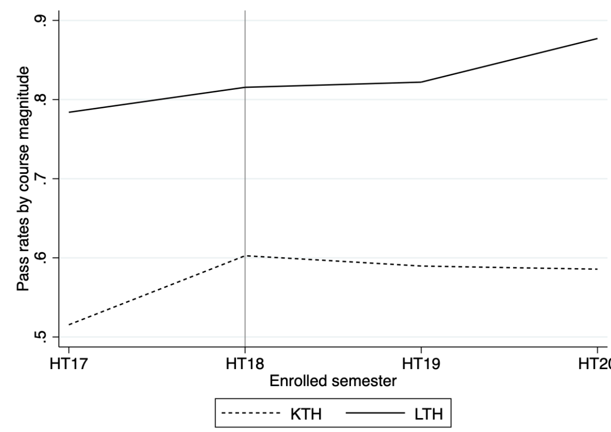

Figure 4: Pass rates in chemical engineering

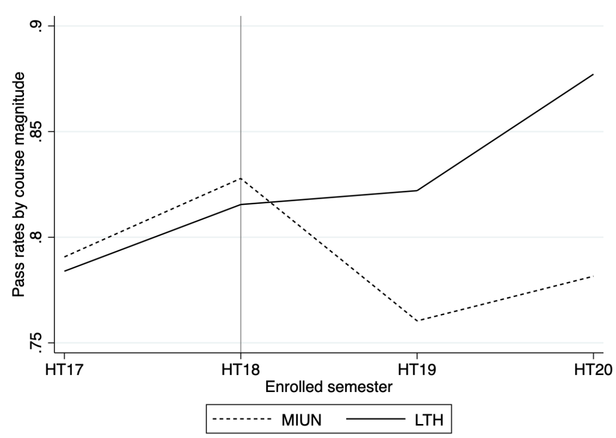

Figure 5: Pass rates in chemical engineering

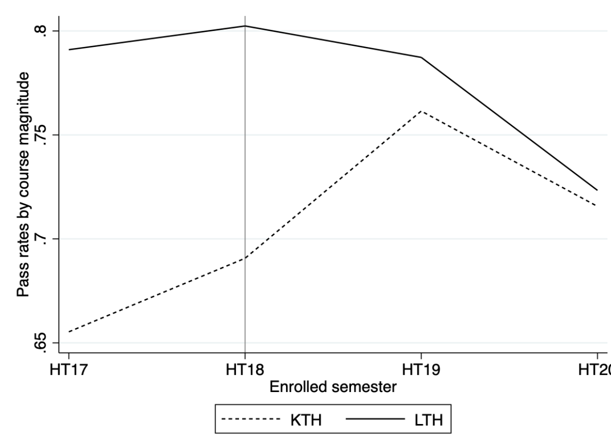

Figure 6: Pass rates in computer science

[10]The F-test compares if the differences between slopes in the pre-treatment period are statistically close to zero. Support of the null would imply that there are no differences in the trajectories of trends between groups.

Presented in Table 3 are programmes in which the linear trend assumption is upheld. The F-test for all programmes can not reject the null hypothesis of linear trends. Note that the null for parallel trends for the chemical engineering programme between LTH (treated) and KTH (control) is excluded from Table 3 as the null is rejected, despite the fact they visually look compatible (see Figure 4.

Most parallel trends between programmes of the treated university LTH and the control group KTH satisfy the condition according to the F-tests. The seemingly good match might lie in that the two universities have more similar curricula in engineering programmes than other universities such as UU. LTH and KTH are undoubtedly large universities that offer many different engineering specialisations. Engineering programmes at LTH and KTH are very similar in terms of admission statistics, such as *BI*, which should suggest that students who attend these schools share many characteristics (Swedish Council for Higher Education, 2022). Universities such as UU, MIUN, and MD offer engineering programmes but not to the same extent. Though, performing a test for parallel trends results in an F-statistic of 128.59 and a p-value of 0.056 for the chemical engineering programme when comparing LTH and MIUN. This result might be somewhat challenging to conceptualise. However, the two programmes share similar course contents—a mixture of introductory quantitative mathematics courses and introductory chemistry courses (see Table 9 to compare courses). Perhaps, these two programmes are suitable for comparison, but with low support for the null hypothesis (that trends are linear pre-treatment), this is not the most prominent result. Nevertheless, with this in mind, support for the null allows for further analysis.

As a robustness check, the academic performance is conditioned on the control variable for proficiency—*BI*—in hopes of making the regression more efficient. The two outer columns in Table 3 are robustness checks in which the trends are conditioned on the covariate. It is important to note that the parallel trend assumption is upheld even unconditionally. Controlling for *BI* is purely a robustness check and not a necessity. Caetano et al. (2022) showed that estimates using conditional parallel trends are not equally robust. However, the parallel trend assumption in our case is fulfilled for the programmes in Table 3 unconditionally as well. By conditioning on *BI*, only a handful of programmes sufficiently uphold the condition of parallel trends. When conditioning on *BI*, the potential outcome in academic performance for programmes changes. If one university has a drastic change in *BI*, then the projected parallel trend in academic performance is altered. The implication of introducing *BI* as a control variable is that schools that previously was comparable—in the sense of a compatible counterfactual—might no longer be compatible matches conditional on *BI*.

Table 3: Linear trends tests of programmes in which the assumption holds. H0: the linear trends are parallel during the pre-treatment period.

	Without Control		Including Control	
Programme (treated/control)	F(1, 1)	Prob>F	F(1, 1)	Prob>F
Biotechnology (LTH/KTH)	1.140	0.479	385.070	0.032
Mechanical engineering (LTH/KTH)	3.840	0.300	463.840	0.030
Industrial engineering (LTH/KTH)	3.000	0.333	104.720	0.062
Industrial engineering (LTH/MIUN)	8.140	0.215	0.000	0.963
Computer science and engineering (LTH/KTH)	4.450	0.282	50.250	0.089
Biomedical engineering (LTH/KTH)	1.610	0.425	0.080	0.830
Electrical engineering (LTH/KTH)	0.490	0.612	2.070	0.387
Chemical engineering (LTH/MIUN)	128.590	0.056	239443.880	0.001

5.2 Average treatment effect on treated

After comparing linear trends visually and statistically, the effect of weighted SweSAT is analysed for those programmes that fulfil the stipulation of linear trends during the pre-treatment period. Table 4 shows the ATET for all of the pertinent programmes and Table 5 includes the control variable *BI*. In Table 4 and 5, a regression comparison between treatment groups is performed in which interaction coefficients—the within and first difference of coefficients—are presented for each year. During the pre-treatment period (before 2019), one would like the interaction coefficients to be close to zero. Such a result would imply that the DiD successfully eliminates the within and first differences as an outcome of suitably comparable programmes. If the effect of treatment is significant, the interaction coefficients will be statistically different from zero once treatment is introduced (2019). *N* represents the sum of comparable examination opportunities (including re-take exams[11]) between treatment groups. Excluding the pre-treatment year 2015, yields no within-

[11] For students enrolled that given year.

difference in the first period. Hence the missing values for the pre-treatment year 2016.

The first regression in Table 4 shows that the ATET is insignificant in the biotechnology programme for the treated LTH and the control KTH. Hence, according to the regression, there is no effect of treatment in the biotechnology programme even though the parallel trend assumption holds. However, the seven remaining regressions show a significant treatment effect on the treated. Further, six out of the seven regressions suggest that the treatment has a negative effect on pass rates. The exception is the chemical engineering programme in the treated university LTH and the control university MIUN. The regression shows an average increase in pass rates by 11.10pp for the treated at the 5% significance level. However, when previously running an F-test for the linear trends in the chemical engineering programme between LTH and MIUN, the outcome is barely in support of the null (see Table 3). Consequently, the positive ATET result of 11.10pp is disputable, and the two programmes might not be suitable for comparability. In the remaining regressions, the average effect of being treated for the treated is negative but varies between programmes. The largest negative effect is present in the mechanical engineering programme (treated—LTH—and control—KTH), in which the ATET is -14.90pp. In the industrial engineering programme in LTH and KTH, the ATET is -2.78pp, which is the least substantial negative treatment effect out of the significant regressions.

The interaction coefficients are close to zero for most programmes during the pre-treatment years, supporting the assertion of parallel trends. However, in the sixth regression—biomedical engineering programme between LTH and KTH—the interaction coefficient for 2018 is significant at the 5% significance level. Fundamentally, this indicates a violation of the parallel trends assumption. Hence, the ATET can not be isolated for this programme. Further, the interaction coefficients for the treatment year 2019 are not statistically different from zero in most regressions. The implication is that the model cannot detect any major differences in trends of academic performance between treatment groups once the weighted SweSAT is implemented. Although, this might be a consequence of an intrinsically small treatment effect, which is quite likely. Only a tiny portion of students are admitted via SweSATQ that otherwise would not have been admitted if the treatment did not occur. Perhaps, therefore, the regressions can not detect a difference between being treated versus not being treated. Nevertheless, knowing that treatment occurs during the enrolment of 2019, the ATET is still distinguishable. The exception is the interaction coefficient between the treated LTH and the control KTH in the mechanical engineering programme, which is significant at 1% significance during the treatment year 2019. The significance implies that the trajectory of the trends is substantially altered, which validates that something occurred during the treatment period. Although, whether it is due to the actual treatment remains inconclusive as the effect is very substantial.

Table 4: Average treatment effect on treated in programmes that fulfil the parallel trend assumption.

	(1) Biotech (LTH/KTH)	(2) Mechanical (LTH/KTH)	(3) Industrial (LTH/KTH)	(4) Industrial (LTH/MIUN)	(5) Computer (LTH/KTH)	(6) Biomedical (LTH/KTH)	(7) Electrical (LTH/KTH)	(8) Chemical (LTH/MIUN)
ATET								
treatment (1=yes)	-0.0055	-0.1490*	-0.0278*	-0.0472**	-0.0890**	-0.0897**	-0.1090**	0.1110*
	(0.00339)	(0.00387)	(0.00168)	(0.000649)	(0.00123)	(0.000778)	(0.000346)	(0.00245)
Controls								
1. 2016	0	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2. 2017	0.0501	0.0196	-0.00697	-0.0141	0.0238	0.00817	-0.000111	0.00990
	(0.0331)	(0.0124)	(0.0108)	(0.0164)	(0.00237)	(0.0276)	(0.0189)	(0.0100)
3. 2018	0.0269	0.0352	0.00376	-0.0139	0.0500	0.0248*	0.00386	0.0462
	(0.0218)	(0.00606)	(0.000446)	(0.00533)	(0.0139)	(0.00195)	(0.0222)	(0.00769)
4. 2019	0.0481	0.152**	0.0289	0.0501	0.123	0.132	0.0926	-0.0381
	(0.0264)	(0.00179)	(0.0121)	(0.0321)	(0.0129)	(0.0181)	(0.0269)	(0.0104)
5. 2020	0.110	0.117	0.0178	-0.00183	0.0673	0.0571	0.0380	-0.000595
	(0.0360)	(0.0270)	(0.0188)	(0.0145)	(0.0221)	(0.0334)	(0.0286)	(0.00714)
_cons	0.684*	0.655*	0.722*	0.807**	0.688*	0.634**	0.645*	0.776**
	(0.0325)	(0.0128)	(0.0147)	(0.00869)	(0.0170)	(0.00885)	(0.0276)	(0.00246)
N	113	172	155	115	168	142	155	91

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Once the control variable, *BI*, is included, the main result of the ATET remains similar for most programmes (see Table 5). Including *BI*, the standard errors are even smaller than compared to the regressions in Table 4. This suggests that the model's precision increases by incorporating a covariate that captures proficiency differences between universities and time. As there is an uncertainty of parallel trends being upheld in some programmes when controlling for *BI*, it is difficult to analyse the ATET. However, some programmes satisfy the condition of parallel trends when integrating *BI*. Namely, industrial engineering (LTH/KTH), industrial engineering (LTH/MIUN), computer science and engineering (LTH/KTH), biomedical engineering (LTH/KTH), and electrical engineering (LTH/KTH) (see Table 3). The interpretation of the significant ATETs in Table 5 is that pass rates on the treated university decreased by the specified number of pp due to the treatment. The ATET between LTH and KTH in industrial engineering is -4.31pp at the 5% significance level. When comparing the biomedical engineering programme between LTH and KTH, the ATET is -12.3pp and significant at the 1% significance level. Further, the ATET in mechanical engineering between the treated LTH and untreated KTH is -16.9pp but only significant at the 5% significance level. In the computer science and engineering programme, the ATET is -11.9pp for the treated LTH when comparing with the control KTH at the 5% significance level. In the biomedical programme—regression six in Table 5—the ATET is -12.3pp and significant at the 0.1% significance level. However, the same problem in the interaction coefficient occurs during the pre-treatment year 2018 as in Table 4. Thus, the parallel trend assumption is assumed to be violated in this programme. Further, the ATET in electrical engineering between LTH and KTH—regression seven in Table 5—is insignificant, suggesting that there is no distinguishing effect of being treated for the treatment group.

Table 5: Average treatment effect, including control variable *BI*, on treated in programmes that fulfil the parallel trend assumption.

	(1) Biotech (LTH/KTH)	(2) Mechanical (LTH/KTH)	(3) Industrial (LTH/KTH)	(4) Industrial (LTH/MIUN)	(5) Computer (LTH/KTH)	(6) Biomedical (LTH/KTH)	(7) Electrical (LTH/KTH)	(8) Chemical (LTH/MIUN)
ATET								
treatment (1=yes)	0.0585	-0.169**	-0.0431*	-0.0538**	-0.119*	-0.123***	-0.0408	0.0823**
	(0.00593)	(0.00196)	(0.00145)	(0.000102)	(0.00242)	(0.000171)	(0.0172)	(0.000641)
Controls								
BI	0.231	-0.0765*	0.166*	0.00648	-0.0775*	-0.193**	0.131	0.00572*
	(0.0314)	(0.00576)	(0.00620)	(0.00142)	(0.00165)	(0.00297)	(0.0304)	(0.000221)
1. 2016	0	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2. 2017	0.00694	-0.00315	0.0210	0.0102	0.0615	-0.0932	-0.0348	0.0468
	(0.0262)	(0.0230)	(0.0156)	(0.0423)	(0.0258)	(0.0187)	(0.00354)	(0.0127)
3. 2018	-0.0166	-0.0143	0.0322	0.00833	0.0787	-0.0912*	-0.0664	0.0789
	(0.00354)	(0.0238)	(0.00522)	(0.0202)	(0.0243)	(0.00563)	(0.0362)	(0.0188)
4. 2019	-0.157	0.147*	0.0555	0.0666	0.190	0.0476	-0.0572	0.00744
	(0.0481)	(0.00751)	(0.0113)	(0.0406)	(0.0226)	(0.00504)	(0.0365)	(0.0228)
5. 2020	-0.155	0.118	0.0423	0.0230	0.145	0.0843*	-0.158	0.0429
	(0.0475)	(0.0347)	(0.00736)	(0.00758)	(0.0169)	(0.00335)	(0.0750)	(0.00726)
_cons	-3.872	2.168*	-2.885*	0.676*	2.219*	4.447**	-1.801	0.662*
	(0.601)	(0.135)	(0.137)	(0.0488)	(0.0547)	(0.0541)	(0.552)	(0.0183)
N	113	172	155	115	168	142	155	91

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In summary, the ATET for the programmes that fulfil the parallel trend assumption is primarily significant and negative. The magnitude of the effect depends on the programme, which is to be expected as the programmes are contrasting in terms of contents. The question is if it makes sense that the ATET is negative by implementing weighted SweSAT admission. There is a worry of heterogeneous shocks, affecting universities uniquely. Such would be the case if the COVID-19 virus had university-specific effects. Hence, regressions excluding the treatment year 2020 are run to alleviate any bias caused by COVID-19 (see Table 7 and 8 in the Appendix). However, the same conclusions are drawn when excluding the enrolment year 2020, i.e., weighted SweSAT has, in general, a significant and negative effect on academic performance.

5.3 Discussion

Reviewing the ATET without the control in programmes that statistically fulfil the parallel trend assumption (see Table 3) rendered a negative and significant effect between 2-15pp. Once incorporating the control variable, *BI*, many of the parallel trends are violated (see Table 3). Intrinsically, this impeaches some programmes' validity of unconditional parallel trends as they might have previously been satisfied due to the exclusion of time-varying university-specific effects. The performed robustness checks imply that the analysis of ATET can only be carried out on a restrictive sample; those where the parallel trend *still* holds conditional on *BI*. Assuming that the covariate is exogenous, the bias should be reduced as the regressions now account for university-specific time-varying effects. Any effect captured by the error term, ε_{st}, is instead accounted for by the control variable, implying a reduced variance in the standard error, thus increasing precision. Yet, the average effect of treatment on the treated when including the control variable still results in a statistically significant negative effect on academic performance between 4-17pp. Further, when excluding the treatment year 2020, factoring out the implications of the COVID-19 virus, the regressions still show a negatively significant ATET. The result of the ATET could, hypothetically, suggest several scenarios about the weighted SweSAT admission trial.

One could be that the treatment of weighted SweSAT admissions actually has a negative effect on academic performance. In theory, students admitted via SweSATQ, that would not have been admitted without treatment, might perform worse during the first two semesters compared to their counterparts that would have been admitted if there was no treatment. Perhaps, enrolling a more versatile student is more desirable to increase pass rates. In other words, enrolling a student that is slightly worse in the quantitative section of the SweSAT exam but better at some linguistic parts might impose higher average pass rates. Reasonably, motivation and study technique might be of greater importance than subject-specific proficiencies during the first two semesters at engineering programmes, as insinuated by Wikström and Wikström (2017). Although, it is conceptually challenging to advocate for the significantly negative effect. Scepticism arises further as the average treatment effect of SweSATQ is expected to be relatively modest. Since the ATET [with control] in, e.g., mechanical engineering programme in LTH with KTH as the control group amounted to -14.9pp [-16.9pp], the study's internal validity is questionable. Seeing as the discrepancy in ATET is large across programmes, it is difficult to advocate any external validity as the policy seems to have affected university programmes differently.

Also, the quantitative qualities tested in the SweSAT might not be sufficiently similar to the qualities necessary to succeed in math-oriented courses in engineering programmes. The quantitative section in the SweSAT tests students in mathematics corresponding to basic mathematics (mathematics 2). However, a minimum of mathematics 4 is a prerequisite to be eligible for engineering programmes. Consequently, SweSATQ might not be representative of quantitative proficient students. As follows, an issue might lie in that the effect of SweSATQ admissions is minimal and not statistically observable. The ATET observed in this paper might therefore depict unobserved time-varying specific effects. Nonetheless, the results could have been different if SweSAT tested students on higher-level mathematics. Alternatively, implementing an admission policy where the courses in mathematics in upper secondary school are used in a selective admission policy might lead to more desirable results, i.e., improved academic performance.

Ultimately, to increase the study's legitimacy, some developments in the research design need to be considered. First, requesting individual-level data on student performance could perhaps increase the precision of the treatment effect. This type of extraction was not possible in this paper, and LADOK departments preferred to share aggregated data on student performance to reduce their workload. If one could obtain individual-level data and control variables for that specific individual, e.g. upper secondary school GPA and SweSAT marks, then perhaps a standard ordinary least squares (OLS) regression would perform better. A drawback with DiD strategies, in general, is the issue of finding a valid control group for the treatment group. One could complement the DiD design by applying propensity score matching to find persuading matches. The researcher could then test how similar universities are based on covariates, e.g., gender composition, age, parental background, and many other regressors. By doing so, one will obtain a propensity score which could indicate suitability in matching. However, the design is limited due to the unavailability of such covariates. DiD is applied in this setting because of its properties in using aggregate data when analysing trajectories in trends to eliminate shared omitted variables in the first difference and school-specific variables in the within difference. Sticking to a regression analysis would certainly demand specifications of many more control variables such as parental background and other socioeconomic covariates in the likes of Wikström and Wikström (2017). Otherwise, the effect of treatment would assuredly be biased. In any case, we argue that including more control variables in this DiD setting is advantageous to account for time-varying university-specific effects. Supposing that the universities are compatible matches, thus eliminating the effects of shared omitted variables, the results might still be biased. Given how dramatically the results contradict prior beliefs about weighted SweSAT admissions' effect on academic performance, the question arises whether the results are unbiased. Any unobserved time-varying school-specific effect—apart from *BI*—is not accounted for in our framework. We do not rule out the possible existence of such variables, which could explain the magnitude of the negative effect. We argue that it is more probable than the causal effect being largely negative. These omitted variables constitute a pitfall in the research design of this paper. For example, our model implicitly assumes that the effect of the COVID-19 virus has an additive homogeneous effect across universities since including control variables that account for the pandemic is difficult to find and even harder to reason for. Maybe, a proxy for technological adaptation within universities could reduce bias and account for how smoothly universities acclimated to home-schooling. However, finding such control is arguably unfeasible.

Nonetheless, even if the model is perfectly specified, including covariates that capture all time-varying university-specific shocks, the effect of SweSATQ on academic performance might not be appreciable. Students admitted via SweSATQ that would otherwise not have been admitted at all represent a vast minority of admitted students. Thus, its' impact on aggregate academic performance might not be able to isolate with statistical significance.

In closing remarks, it is of interest to see if weighted admission policies could have long-lasting effects on academic performance. Since the policy intervention of weighted SweSAT only took place during the enrollment of 2019 and 2020, only short-term effects can be scrutinised in the investigated programmes. Suppose that weighted SweSAT replaces SweSAT as a new admission channel indefinitely, then upper secondary students might adapt their way of study. Perhaps, students enthusiastic about studying engineering programmes in higher education might focus more on quantitative studies during their stay at upper secondary school. Such a behavioural change might lead to the desired effect of increasing student performance—namely pass rates—in universities. Further, if different universities implemented different weights, it might be possible to identify if there exists a weight optimum of quantitative and verbal qualities. Additionally, it would also be appealing to see whether a weighted admission policy affects GPA for students at the university and not only pass rates. Overall, the SweSATQ admission might have a more apparent effect on GPA compared to pass rates. However, in the context of the paper, the link between student retention and academic performance is believed to be via pass rates.

6 Conclusion

The paper aims to investigate the effect of weighted SweSAT admission on academic performance in engineering programmes at universities in Sweden. In particular, to see if academic performance increased by the treatment and, in turn, improved the retention rate of engineering students. Albeit, the effect of weighted SweSAT admission remains unsolved as doubtful results impair conclusions. To answer the research question at issue, we find no evidence that supports the supposition of increased academic performance by the policy implementation. Several arguments are provided in the paper that question the internal and external validity of the study. The paper should instead be used as a starting point in evaluating admission selection policies at Swedish universities. Despite questionable results, the paper still sheds light on the advantages of a DiD design in a policy evaluation context. The research design successfully accounts for university and time-specific effects. However, we encourage future research to extend the model by incorporating methods to account for time-varying school-specific effects, identified as the paper's major pitfall.

One thing is for certain, the demand for engineers remains high and will continue to increase. Additional research on the topic is necessary to help decision-makers achieve a successful admission policy that increases student retention and the number of graduated engineers.

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Appendix

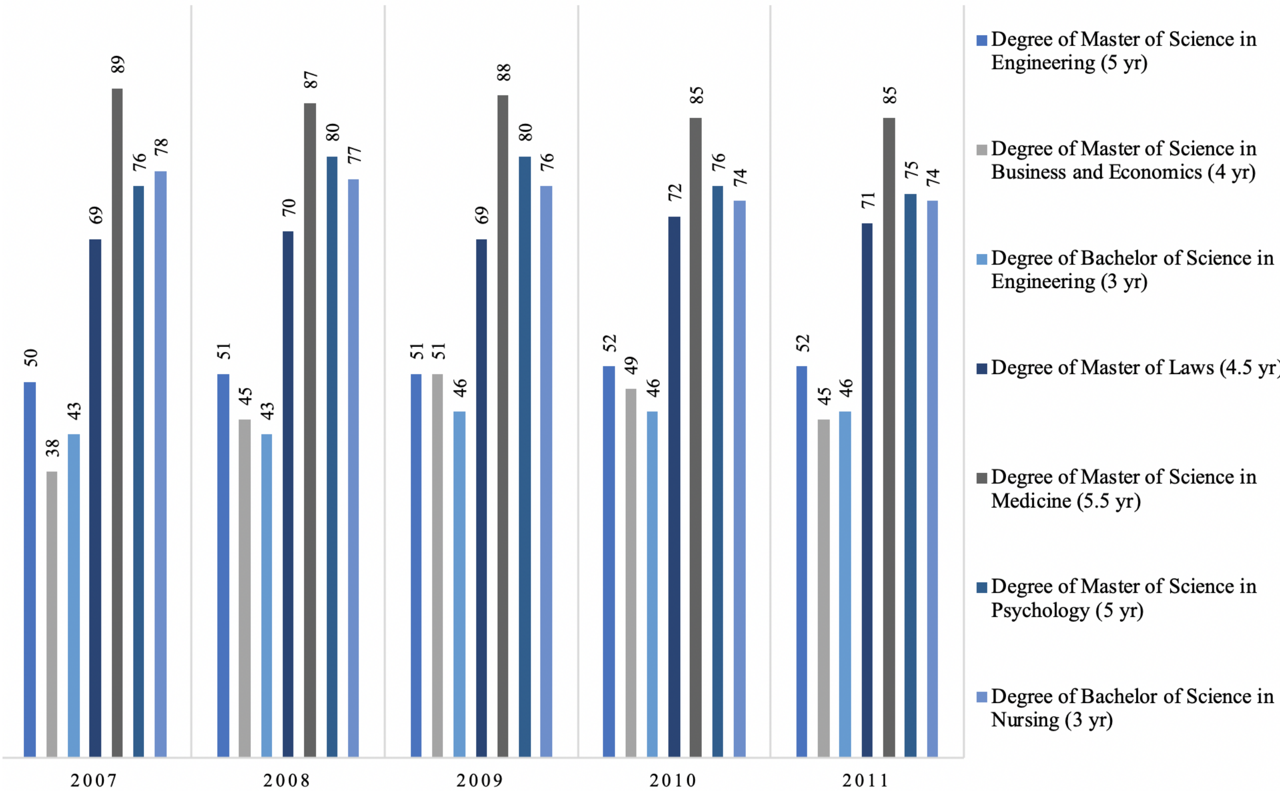

Figure 7: First-year students in professional degree programmes by graduated in the followed up years 2009/10–2019/20 in per cent (followed up years = programme nominal length of study + three years) (Statistics Sweden, 2021).

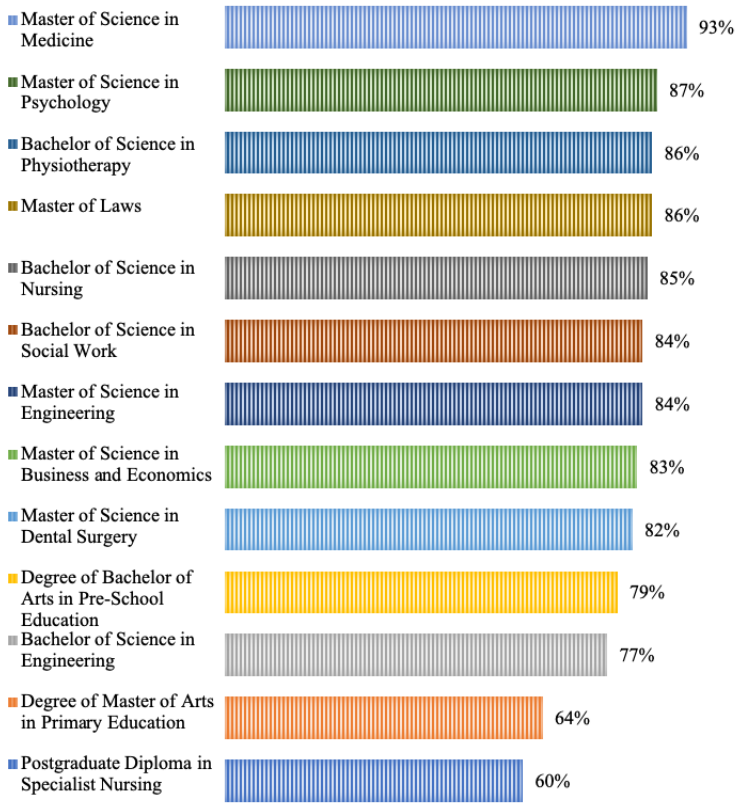

Figure 8: Programme beginners year 2016, in professional degree programmes, by retention rate year 2017 in per cent(Swedish Higher Education Authority, 2019).

Table 6: Treated and untreated engineering programmes

Treatment					
Programmes \ Universities	Chalmers	Luleå	Lund	Umeå	Uppsala
Biomedical Engineering	X	-	X	-	-
Biotechnology	X	-	X	X	-
Chemical Engineering	X	-	X	-	X

Continued on next page

Table 6: Treated and untreated engineering programmes (Continued)

Computer Science and Engineering	X	X	X	-	-
Electrical Engineering	X	X	X	-	-
Engineering Physics	X	X	X	X	X
Industrial Engineering	X	X	X	X	-
Information and Communication Technology	X	-	X	-	-
Mechanincal Engineering	X	X	X	-	-
Control					
Programmes \ Universities	Mälardalen	KTH			
Biomedical Engineering	-	X			
Biotechnology	-	X			
Chemical Engineering	-	X			

Continued on next page

Table 6: Treated and untreated engineering programmes (Continued)

Computer Science and Engineering	-	X
Electrical Engineering	-	X
Engineering Physics	-	X
Industrial Engineering	X	X
Information and Commu-nication Technology	-	X
Mechanincal Engineering	-	X

Table 7: Average treatment effect on treated in programmes that fulfil the linear trends assumption (excluding treatment year 2020).

	(1) Biotech (LTH/KTH)	(2) Mechanical (LTH/KTH)	(3) Industrial (LTH/KTH)	(4) Industrial (LTH/MIUN)	(5) Computer (LTH/KTH)	(6) Biomedical (LTH/KTH)	(7) Electrical (LTH/KTH)	(8) Chemical (LTH/MIUN)
ATET								
treatment (1=yes)	0.00498	-0.174**	-0.0212*	-0.0983**	-0.0800**	-0.144**	-0.107**	0.0939*
	(0.00430)	(0.00261)	(0.00142)	(0.000215)	(0.000901)	(0.000532)	(0.000239)	(0.00187)
Controls								
1. 2016	0	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2. 2017	0.0501	0.0196	-0.00697	-0.0141	0.0238	0.00817	-0.000111	0.00990
	(0.0331)	(0.0124)	(0.0108)	(0.0164)	(0.00237)	(0.0276)	(0.0189)	(0.0100)
3. 2018	0.0269	0.0352	0.00376	-0.0139	0.0500	0.0248*	0.00386	0.0462
	(0.0218)	(0.00606)	(0.000446)	(0.00533)	(0.0139)	(0.00195)	(0.0222)	(0.00769)
4. 2019	0.0444	0.165	0.0256	0.0834	0.118	0.156*	0.0918	-0.0299*
	(0.0310)	(0.0140)	(0.0153)	(0.00882)	(0.0174)	(0.00866)	(0.0277)	(0.00164)
_cons	0.681*	0.648*	0.718*	0.806**	0.686*	0.627**	0.639*	0.777**
	(0.0324)	(0.0129)	(0.0147)	(0.00870)	(0.0170)	(0.00884)	(0.0276)	(0.00244)
N	95	142	129	94	140	117	131	75

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Average treatment effect, including control variable *BI*, on treated in programmes that fulfil the linear trends assumption(excluding treatment year 2020).

	(1) Biotech (LTH/KTH)	(2) Mechanical (LTH/KTH)	(3) Industrial (LTH/KTH)	(4) Industrial (LTH/MIUN)	(5) Computer (LTH/KTH)	(6) Biomedical (LTH/KTH)	(7) Electrical (LTH/KTH)	(8) Chemical (LTH/MIUN)
ATET								
treatment (1=yes)	0.0548	-0.198*	-0.0254*	-0.0954**	-0.126*	-0.0791*	0.0363	0.0676**
	(0.00464)	(0.00411)	(0.00131)	(0.000934)	(0.00218)	(0.00514)	(0.0124)	(0.000302)
Controls								
BI	0.261	-0.0822	0.186**	0.00292	-0.0806**	-0.520*	0.202	0.00557*
	(0.0327)	(0.00667)	(0.000719)	(0.000731)	(0.000867)	(0.0398)	(0.0181)	(0.000205)
1. 2016	0	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
2. 2017	0.00145	-0.00483	0.0244	-0.00312	0.0629	-0.266	-0.0536	0.0459
	(0.0248)	(0.0239)	(0.0176)	(0.0285)	(0.0272)	(0.0284)	(0.0125)	(0.0120)
3. 2018	-0.0222	-0.0179	0.0357	-0.00385	0.0798	-0.289*	-0.105	0.0781
	(0.00727)	(0.0263)	(0.00460)	(0.00648)	(0.0250)	(0.0169)	(0.0284)	(0.0181)
4. 2019	-0.179	0.161	0.0490*	0.0870	0.195	-0.142	-0.158	0.0135
	(0.0423)	(0.0213)	(0.00335)	(0.0146)	(0.0207)	(0.0204)	(0.0297)	(0.0146)
_cons	-4.448	2.271*	-3.327**	0.747*	2.279*	10.91*	-3.141	0.666*
	(0.629)	(0.154)	(0.0117)	(0.0285)	(0.0394)	(0.783)	(0.331)	(0.0177)
N	95	142	129	94	140	117	131	75

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Course Specification for university programmes

Course Name	Course Code	ECTS Credits
BTH - Blekinge Institute of Technology		
Industrial Engineering		
Basic Physics	FY1420	4
Basic Mathematics	MA1472	4
Technical Introduction in Industrial Engineering	MT1466	8
Introduction to Industrial Engineering and Management	IY1404	8
Linear Algebra 1	MA1448	6
Calculus 1	MA1444	6
Integrated project I: Project Organisation	IY1409	12
Leadership and Projects	IY1424	4
Communication for Engineers	SV1406	4
Electrical Principals, basic course	ET1479	4
Fundamentals of industrial economics	IY1418	6
Basic Mathematics	MA1480	4
Technical Introduction Course with Engineering Methodology	TE1420	8

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Table 9: Course Specification for university programmes (Continued)

Managerial Economics and Strategy	IY1417	6
Physics for Engineers 1	FY1422	4
Introductory programming in Java	DV1559	8
Firms and organization	IY1416	6
Manufacturing Technology	MT1462	6
Mathematical Problem Solving	MA1486	4
Technical Introduction Course with Engineering Methodology	TE1421	8
Basic Physics	FY1428	6
Programming and Problem Solving with Python	DV1574	6
Discrete Mathematics	MA1446	6
Basic Physics	FY1431	6
Calculus 2	MA1445	6
Firms and Organization	IY1439	6
Calculus 2	MA1494	6
Mechanical Engineering		
Basic Physics	FY1420	4
Basic Mathematics	MA1472	4

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Table 9: Course Specification for university programmes (Continued)

Technical Introduction in Mechanical Engineering, Bachelor	MT1495	10
Linear Algebra 1	MA1448	6
Environmental Strategy and Sustainable Developement	SL1404	6
Calculus 1	MA1444	6
Computer Aided Engineering	MT1449	8
Dynamics	MT1457	6
Communication for Engineers	SV1406	4
Manufacturing Technology	MT1462	6
Basic Mathematics	MA1480	4
Dynamics	MT1502	6
Basic Physics	FY1428	6
Mathematical Problem Solving	MA1486	4
Technical Introduction in Mechanical Engineering	MT1512	10
Basic Programming in Matlab	ET1540	6
Computer aided Design and Drawing Standards, part 1	MT1519	10
Basic Physics	FY1431	6
Technical Introduction in Mechanical Engineering	MT1551	8

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Table 9: Course Specification for university programmes (Continued)

Programming and Problem Solving with Python	DV1574	6
Computer Aided Design and Engineering 1	MT1549	8
Physics - waves and energy	FY1433	6
Matlab with Mathematical and Technical applications	ET1549	4
CTH - Chalmers University of Technology		
Biomedical Engineering		
Introductory course in biomedical engineering	EEN080	7.5
Medicine for engineers	EEN085	7.5
Introductory course in mathematics	TMV157	7.5
Calculus in one variable	TMV137	7.5
Introductory course in programming	DAT445	7.5
Linear algebra	TMV143	7.5
Biomedical electronics	EEN075	7.5
Basic physics	MCC160	7.5
Multivariable analysis	TMA044	7.5
Biotechnology		
Chemistry with biochemistry	KBT250	21

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Table 9: Course Specification for university programmes (Continued)

Multivariable calculus	MVE470	7.5
Introductory biotechnology	KLI060	3
Mechanics	FTF195	6
Physics	TIF370	6
Single variable calculus and analytical geometry	MVE460	7.5
Introduction to cell and molecular biology	UCM010	7.5
Linear algebra and calculus	MVE465	7.5
Chemical Engineering		
Chemistry with biochemistry	KBT260	7.5
Multivariable calculus	MVE470	7.5
Single variable calculus and analytical geometry	MVE460	7.5
Physics	FFY401	7.5
Physics	FFY402	7.5
Linear algebra and calculus	MVE465	7.5
Perspectives on chemical engineering	KBT270	6
Perspectives on chemical engineering	KBT271	6
Computer Science and Engineering		

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Table 9: Course Specification for university programmes (Continued)

Introduction to functional programming	TDA555	7.5
Object oriented programming	DAT043	7.5
Introduction to object oriented programming	DAT044	7.5
Introduction to discrete mathematics	TMV210	7.5
Calculus	TMV170	7.5
Introduction to discrete mathematics	TMV211	7.5
Introduction to computer engineering	EDA452	7.5
Computer communication	EDA343	7.5
Linear Algebra	TMV216	7.5
Embedded systems programming	EDA481	7.5
Machine oriented programming	EDA482	7.5
Electrical Engineering		
Circuit analysis	EMI084	3.7
Object-oriented programming	TDA547	7.5
Introductory course in programming	DAT445	7.5
Technical communication	FSP025	3.8

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Table 9: Course Specification for university programmes (Continued)

Linear algebra	TMV141	7.5
Linear algebra	TMV143	7.5
Technical project in electrical engineering	MCC145	7.5
Introductory course in mathematics	TMV157	7.5
Fundamentals of digital systems and computers	EDA216	7.5
Calculus in one variable	TMV137	7.5
Physics	FFY401	7.5
Multivariable analysis	TMA044	7.5
Engineering Physics		
Tools of Engineering Physics	TIF275	10.5
Multivariable analysis	MVE035	6
Linear algebra	MVE670	6
Linear algebra and geometry	TMA660	4.5
Mechanics 2	FFM521	6
Tools of engineering physics	TIF276	9
Mechanics 2	TIF375	6
Introductory mathematical analysis	TMA970	6
Linear algebra and numerical analysis	TMA671	7.5

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Table 9: Course Specification for university programmes (Continued)

Linear algebra and numerical analysis	TMA672	7.5
Mathematical statistics	TMA321	4.5
Mechanics 1	FFM516	7.5
Computer programming	TIN212	6
Computer programming	TIN213	6
Computer programming	TIN214	6
Computer programming and numerical analysis	SEE125	9
Real analysis	TMA976	6
Industrial Engineering		
Introductory course in mathematics	MVE012	7.5
Economic analysis 2: Financial statements	IDY029	7.5
Introduction to programming	TDA144	7.5
Introductory course in mathematics	MVE013	6
Linear algebra	MVE023	6
Introduction to engineering economics and organisation	TEK040	7.5
Programmed systems	TDA143	7.5
Financial statement analysis and corporate valuation	TEK730	7.5

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Table 9: Course Specification for university programmes (Continued)

Introduction industrial economy	TEK925	6
Operations management	TEK930	6
Economic analysis 1: Managerial economics	IDY023	7.5
Linear algebra I	MVE021	7.5
Linear Algebra	MVE022	7.5
Profitability analysis and financial management	IDY024	7.5
Project management, basic course	TEK935	6
Sustainability transitions	TEK940	6
Calculus in one variable	MVE016	7.5
Physics for engineers 1: Physics for sustainable development	TIF190	7.5
Calculus in one variable	MVE017	7.5
Calculus in one variable	MVE018	6
Multivariable calculus	MVE660	6
Financial management	TEK950	6
Financial statement analysis and corporate valuation	TEK945	6
Information and Communication Technology		

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Table 9: Course Specification for university programmes (Continued)

Introduction to computer engineering	EDA433	7.5
Physics for engineers 1: Physics for sustainable development	DAT216	7.5
Machine oriented programming	DAT017	7.5
Object-oriented programming	TDA545	7.5
Communication and professional development	LSP310	7.5
Introductory software development	TDA548	7.5
Linear algebra	TMV206	7.5
Object-oriented programming, advanced course	TDA550	7.5
Object-oriented programming and design	TDA551	7.5
Object-oriented programming and design	TDA552	7.5
Discrete mathematics	TMV200	7.5
Object-oriented programming project	TDA367	7.5
Mechanical Engineering		

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Table 9: Course Specification for university programmes (Continued)

Introduction to mechanical engineering	MMF176	7
Statics and solid mechanics	MTM021	7.5
Programming in matlab	TME136	4
Linear algebra	TMV166	7.5
Introductory course in mathematics	TMV225	7.5
Solid mechanics	MTM026	7.5
Computer aided design (CAD)	PPU156	4
Calculus in several variables	MVE255	7.5
Calculus in a single variable	TMV151	7.5
KTH - Royal Institute of Technology		
Biomedical Engineering		
Calculus in One Variable	SF1625	7.5
Engineering Introduction	HL1200	6
Electrical Principals and Measurement	HE1200	9
Programme Integrating course in Medical Engineering	CM1004	3
Medicine and Medical Engineering, Basic Course	HL1201	12

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Table 9: Course Specification for university programmes (Continued)

Basic Medicine	HL1001	7.5
Computer Programming, Basic Course	HI1024	8
Algebra and Geometry	SF1624	7.5
Thermodynamics, Basic Course	HL1204	6
Computer Programming, Basic Course	HI1200	6
Introduction to Biotechnology	CB1040	6
Calculus in Several Variables	SF1626	7.5
Mechanics, Smaller Course	SG1102	9
Biotechnology		
Biochemistry	BB1150	7.5
Microbiology	BB1030	9
Eucaryotic Cell Biology	BB1160	7.5
Gene Technology	BB1190	7.5
The Engineer in Focus	BB1170	6
Organic Chemistry, Basic Concepts and Practice	KD1230	6
Introductory Chemistry	KD1020	6
Introduction to Chemical Engineering	KE1180	7.5
Calculus in One Variable	SF1625	7.5
Chemical Engineering		

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Table 9: Course Specification for university programmes (Continued)

Calculus in One Variable	SF1625	7.5
Algebra and Geometry	SF1624	7.5
Organic Chemistry, Basic Concepts and Practice	KD1230	6
Biotechnology	BB1050	6
Perspectives on Research and Innovation	KA1030	6
Project Management for Chemistry Engineering Students	ME1402	6
Engineering Chemistry	KE1140	14
Chemical Analysis	KD1280	10.5
Calculus in Several Variables	SF1626	7.5
Computer Science and Engineering		
Mathematics, Basic course, with Discrete Mathematics	SF1671	7.5
Algorithms and Data Structures	DD1338	6
Programme Integrating Course in Computer Science Engineering	DD1390	6
Writing in the Engineering Profession	DA1600	4.5

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Table 9: Course Specification for university programmes (Continued)

Calculus in One Variable	SF1625	7.5
Programming	DD1337	7
Human-Computer Interaction	DH1620	6
Project in Introduction to Computer Science	DD1349	3
Linear Algebra	SF1604	7.5
Parallel and Concurrent Programming in Introduction to Computer Science	DD1396	3
Algebra and Geometry	SF1624	7.5
Numerical Methods, Basic Course	SF1547	6
Electrical Engineering		
Algebra and Geometry	SF1624	7.5
Programming Techniques and C	DD1316	6
Calculus in One Variable	SF1625	7.5
Project Course in Electrical Engineering	EH1010	7.5
Electrical Circuit Analysis, Extended Course	EI1110	9
Calculus in Several Variables	SF1626	7.5
Global Impact of Electrical Engineering	EH1110	7.5

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Table 9: Course Specification for university programmes (Continued)

Introduction to Computing Systems Engineering	EP1200	6
Digital design	IE1205	6
Engineering Physics		
Calculus II, part 1	SF1602	9
Fundamentals of Programming and Computer Science	DD1345	7.5
Fundamentals of Programming	DD1331	5
Linear Algebra	SF1672	7.5
Linear Algebra	SF1604	7.5
Classical Physics	SK1102	12
Analysis in one variable	SF1673	7.5
Classical Physics	SK1104	7.5
Thermodynamics	SI1121	6
Calculus II, part 2	SF1603	9
Multivariable Calculus	SF1674	7.5
Mechanics	SG1130	9
Mechanics I	SG1112	9
Probability theory and statistics	SF1901	6
Probability Theory and Statistics	SF1922	6

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Table 9: Course Specification for university programmes (Continued)

Vector Analysis	SI1146	4
Experimental Physics	SK1105	4
Industrial Engineering		
Calculus in One Variable	SF1625	7.5
Industrial Project Management	ME1306	7.5
Introduction to Industrial Engineering and Management	ME1314	9
Programming Techniques and Matlab	DD1315	7.5
Calculus in Several Variables	SF1626	7.5
Industrial Marketing for I	ME1315	6
Introduction to Industrial Engineering and Management	ME1305	7.5
Mechanics	SG1109	8
Algebra and Geometry	SF1624	7.5
Industrial Marketing for I	ME1307	7.5
Information and Communication Technology		
Engineering Skills for ICT	II1304	7.5
Introduction to IT	II1306	1.5
Computer Hardware Engineering	IS1200	7.5
Digital Design	IE1204	7.5

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Table 9: Course Specification for university programmes (Continued)

Programming	ID1018	7.5
Programming I	D1018	7.5
Discrete Mathematics	SF1610	7.5
Calculus in One Variable	SF1625	7.5
Basic Course in Mathematics	SF1689	6
Embedded Electronics	IE1206	7.5
Mathematics, Basic Course	SF1659	4.5
Algebra and Geometry	SF1624	7.5
Mechanical Engineering		
Algebra and Geometry	SF1624	7.5
Numerical Methods and Basic Programming	SF1511	9
Introduction to Mechanical Engineering	MJ1103	10.5
Calculus in Several Variables	SF1626	7.5
Mechanics	SG1130	9
Programming Techniques	DD1310	6
Practical Introduction to Energy Technology	MJ1104	6
Calculus in One Variable	SF1625	7.5
Physics I	SK1112	9
Mechanical Engineering, introductory course	MF1001	9

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Table 9: Course Specification for university programmes (Continued)

Electromagnetism and Waves	SK1110	7.5
LTU - Luleå University of Technology		
Computer Science and Engineering		
Introduction to Programming	D0009E	7.5
Object-oriented Programming and Design	D0010E	7.5
Computer and engineering science	D0015E	7.5
Calculus	M0029M	7.5
Differential calculus	M0047M	7.5
Physics 1	F0004T	7.5
Digital Design	D0011E	7.5
Discrete Mathematics	M0009M	7.5
Linear Algebra and Calculus	M0030M	7.5
Linear Algebra and Calculus	M0048M	7.5
Industrial Engineering		
Calculus	M0029M	7.5
Linear Algebra and Differential Equations	M0031M	7.5
Industrial Management with a Sustainability Perspective	G0010N	7.5

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Table 9: Course Specification for university programmes (Continued)

Linear Algebra and Differential Equations	M0049M	7.5
Principles of project- and industrial business management	R0005N	7.5
Operations Management	T0008N	7.5
Differential calculus	M0047M	7.5
Industrial management control and finance	R0028N	7.5
Physics 1	F0004T	7.5
Physics 3	F0006T	7.5
Industrial management	E0009N	7.5
Operations management and strategy	K0019N	7.5
Linear Algebra and Calculus	M0030M	7.5
Functions of Several Variables and Computer Tools	M0032M	7.5
Linear Algebra and Calculus	M0048M	7.5
Multivariable calculus	M0055M	7.5
Mechanical Engineering		
Introduction to technology	M0009T	7.5
Physics 2	F0005T	7.5
Calculus	M0029M	7.5

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Table 9: Course Specification for university programmes (Continued)

Linear Algebra and Differential Equations	M0031M	7.5
Differential calculus	M0047M	7.5
Linear Algebra and Differential Equations	M0049M	7.5
Physics 1	F0004T	7.5
Physics 3	F0006T	7.5
Programming and Digitalisation	D0028E	7.5
Linear Algebra and Calculus	M0030M	7.5
Principles of project- and industrial business management	R0005N	7.5
Linear Algebra and Calculus	M0048M	7.5
Industrial Management with a Sustainability Perspective	G0010N	7.5
LTH - Lund Faculty of Engineering		
Biomedical Engineering		
Introduction to Biomedical Engineering	EITA01	12
Calculus in One Variable	FMAA01	15
Calculus in One Variable A1	FMAB45	5

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Table 9: Course Specification for university programmes (Continued)

General and Organic Chemistry	KOKA20	7.5
Thermodynamics, Waves and Optics	FAFA65	7.5
Calculus in One Variable A3	FMAB60	5
Programming, First Course	EDA011	7.5
Programming, First Course	EDAA50	7.5
Clinical Training in Biomedical Engineering	EXTA56	5
Calculus in One Variable A2	FMAB50	5
Linear Algebra	FMA420	6
Linear Algebra	FMAB20	6
Biotechnology		
Introduction to Biotechnology	KBTA05	7.5
General Chemistry	KOOA15	7.5
Calculus in One Variable B1	FMAB65	7.5
Calculus in One Variable	FMAA05	15
Linear Algebra with Introduction to Computer Tools	FMAA20	7.5
Introductory Chemistry	KOOA10	7.5
Life Science Processes and Calculations	KLGA01	7.5
Calculus in One Variable B2	FMAB70	7.5

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Table 9: Course Specification for university programmes (Continued)

Introduction to Programming Using Python	EDAA70	7.5
Organic Chemistry	KOKA25	7.5
Introductory Chemistry	KOOA20	7.5
Chemical Engineering		
Introduction to Chemical Engineering	KETA05	7.5
General Chemistry	KOOA15	7.5
Calculus in One Variable B1	FMAB65	7.5
Calculus in One Variable	FMAA05	15
Linear Algebra with Introduction to Computer Tools	FMAA20	7.5
Introductory Chemistry	KOOA10	7.5
Organic Chemistry	KOKA25	7.5
Introductory Chemistry	KOOA20	7.5
Calculus in One Variable B2	FMAB70	7.5
Introduction to Programming Using Python	EDAA70	7.5
Chemical Process Calculations	KETA10	7.5
Computer Science and Engineering		
Computer Introduction	EDA070	3

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Table 9: Course Specification for university programmes (Continued)

Photonics	FAFA60	5
Computer Introduction	EDAA60	3
Calculus in One Variable	FMAA05	15
Programming - Second Course	EDAA01	7.5
Calculus in One Variable B1	FMAB65	7.5
Programming, First Course	EDA016	7.5
Evaluation of Software Systems	EDAA35	7
Introduction to Programming	EDAA45	7.5
Cognition	TEK210	4.5
Discrete Structures in Computer Science	EDAA40	5
Cognition	EXTA65	4.5
Linear Algebra	FMA420	6
Linear Algebra	FMAB20	6
Calculus in One Variable B2	FMAB70	7.5
Electrical Engineering		
Calculus in One Variable	FMAA05	15
Electronics	ESS010	15
Electronics	EITA35	15
Calculus in One Variable B1	FMAB65	7.5
Programming, First Course	EDA017	9

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Table 9: Course Specification for university programmes (Continued)

Programming, First Course	EDAA55	9
Linear Algebra	FMA420	6
Linear Algebra	FMAB20	6
Calculus in One Variable B2	FMAB70	7.5
Calculus in Several Variables	FMA430	6
Calculus in Several Variables	FMAB30	6
Physics - Mechanics and Waves	FAFA01	9
Engineering Physics		
Linear Algebra	FMA420	6
Calculus in Several Variables	FMA430	6
Linear Algebra	FMAB20	6
Calculus in Several Variables	FMAB30	6
Calculus in One Variable B1	FMAB65	7.5
Engineering Mechanics I	FMEA35	6
Calculus in One Variable	FMAA05	15
Engineering Mechanics - Statics and Particle Dynamics	FMEA05	6
Calculus in Several Variables	FMAB35	7.5
Concepts in Quantum Physics	FAFA55	9
Programming, First Course	EDA017	9
Programming, First Course	EDAA55	9
Waves and Optics	FAFF30	9

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Table 9: Course Specification for university programmes (Continued)

Calculus in One Variable B2	FMAB70	7.5
Waves and Optics	FAFF40	7.5
Industrial Engineering		
Calculus in One Variable	FMAA05	15
Calculus in Several Variables	FMA430	6
Calculus in Several Variables	FMAB30	6
Calculus in One Variable B1	FMAB65	7.5
Programming, First Course	EDAA55	9
Managerial Economics	MIOA01	9
Engineering Mechanics, Basic Course	FMEA10	9
Linear Algebra	FMA420	6
Energy and Environmental Physics	FAFA15	9
Linear Algebra	FMAB20	6
Energy and Environmental Physics	FAFA75	9
Calculus in One Variable B2	FMAB70	7.5
Energy and Environmental Physics	FAFA76	7.5
Management Organization	MIO022	6
Management Organization	MIOF20	6
Information and Communication Technology		

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Table 9: Course Specification for university programmes (Continued)

Communication Systems	ETS130	7.5
Programming, First Course	EDA017	9
Communication Systems	EITA55	7.5
Programming, First Course	EDAA55	9
Calculus in One Variable B1	FMAB65	7.5
Programming - Second Course	EDAA01	7.5
Calculus in One Variable	FMAA05	15
Linear Algebra	FMA420	6
Photonics	FAFA60	5
Introduction to Programming	EDAA45	7.5
Design of Systems for Digital Transformation	EITA65	15
Cognition	TEK210	4.5
Cognition	EXTA65	4.5
Linear Algebra	FMAB20	6
Calculus in One Variable B2	FMAB70	7.5
Cognition and Interaction Design	MAMA20	7.5
Information Transmission	EIT100	7.5
Information Transmission	EITA30	7.5
Linear Algebra with Numerical Applications	FMAA21	7.5

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Table 9: Course Specification for university programmes (Continued)

Discrete Structures	EDAA75	7.5
Software Engineering - Methodology	ETSA02	6
Software Engineering - Methodology	ETSA03	6
Mechanical Engineering		
Manual and Computer Aided Drafting	MMK010	6
Calculus in One Variable	FMAA01	15
Manual and Computer Aided Drafting	MMKA25	6
Calculus in One Variable A1	FMAB45	5
Programming, First Course	EDAA65	6
Introduction to Mechanical Engineering	MMTA02	6
Programming, First Course	EDA501	6
Calculus in One Variable A3	FMAB60	5
Managerial Economics	MIOA01	9
Linear Algebra	FMA420	6
Calculus in Several Variables	FMA430	6
Linear Algebra	FMAB20	6
Calculus in Several Variables	FMAB30	6
Calculus in One Variable A2	FMAB50	5
Applied Optics and Waves	FAF260	6

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Table 9: Course Specification for university programmes (Continued)

Applied Optics and Waves	FAFA80	6
MIUN - Mid Sweden University		
Chemical Engineering		
Physics BA (A), Engineering Methods	FY032G	3
Mathematics GR (A), Algebra	MA115G	3
Chemistry BA (A), Engineering Chemistry	KE026G	12
Industrial Engineering and Management Ba (A), Introduction to Project Based Product Development	IG028G	6
Mathematics BA (A), Linear Algebra I	MA073G	6
Chemistry BA (B), Chemical Equilibrium and Analytical Chemistry	KE027G	12
Chemical Engineering BA (A), Engineering Chemistry	KT018G	6
Mathematics BA (A), Integral Calculus	MA131G	6
Physics BA (A), Engineering Methods	FY033G	6

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Table 9: Course Specification for university programmes (Continued)

Chemistry BA (A), Sustainable Development for Engineers	KE032G	3
Chemistry BA (B), Chemical Equilibrium Theory	KE036G	4,5
Chemistry BA (A), General Chemistry	KE035G	9
Electrical Engineering		
Computer Engineering BA (A), Basic Computer Science	DT027G	6
Physics BA (A), Engineering Methods	FY033G	6
Mathematics GR (A), Algebra	MA115G	3
Computer Engineering BA (A), Introduction to Programming	DT028G	6
Mathematics BA (A), Linear Algebra I	MA073G	6
Chemistry BA (A), Sustainable Development for Engineers	KE032G	3
Electrical Engineering BA (A), Circuit Theory and Electronics	ET047G	6

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Table 9: Course Specification for university programmes (Continued)

Industrial Engineering and Management Ba (A), Introduction to Project Based Product Development	IG028G	6
Electrical Engineering BA (A), Digital Electronics with PLC	ET099G	6
Mathematics BA (A), Integral Calculus	MA131G	6
Physics BA (A), Mechanics I	FY015G	6
Physics BA (A), Electromagnetics and Waves I	FY024G	6
Physics BA (A), Electromagnetics and Waves I	FY025G	6
Industrial Engineering		
Physics BA (A), Engineering Methods	FY033G	6
Mathematics GR (A), Algebra	MA115G	3
Physics BA (A), Mechanics I	FY015G	6
Mathematics BA (A), Linear Algebra I	MA073G	6
Chemistry BA (A), Sustainable Development for Engineers	KE032G	3

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Table 9: Course Specification for university programmes (Continued)

Industrial Engineering and Management Ba (A), Introduction to Project Based Product Development	IG028G	6
Mathematics BA (A), Integral Calculus	MA131G	6
MD - Mälardalen University		
Industrial Engineering		
Introduction to Engineering and Management	OAH103	7.5
Basic Electrical Engineering	ERA100	7.5
Introduction to Industrial Engineering and Management	IEO115	7.5
Single Variable Calculus	MAA149	7.5
Markets and Companies	FOA131	7.5
Applied Thermodynamics	ERA102	7.5
Vector Algebra	MAA150	7.5
Fundamentals of programming	DVA127	7.5
Mechanics of Fluids	ERA101	7.5
Technology and Society	IEO101	7.5
Thermodynamics	FYA011	7.5

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Table 9: Course Specification for university programmes (Continued)

Innovation Technology in an Industrial Context	INO126	7.5
Envariabelkalkyl	MAA151	7.5
Calculus of Several Variables	MAA152	7.5
Sustainable Development	OAH117	7.5
Introduction to Technical Projects	OAH116	7.5
UMU - Umeå Institute of Technology		
Biotechnology		
Introduction for Engineers in Biotechnology	5MO072	5
Fundamentals of Chemistry with environmental and societal perspectives	5KE105	7.5
Introduction for Engineers in Biotechnology	5MO072	7.5
Fundamentals of Chemistry	5KE165	15
Introductory programming in Python and Matlab	5DV105	7.5
Linear Algebra	5MA019	7.5
Linear Algebra	5MA160	7.5
Introductory programming in Python and Matlab	5DV176	7.5

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Table 9: Course Specification for university programmes (Continued)

Calculus in One Variable 1	5MA009	7.5
Statistics for Engineers	5MS008	7.5
Calculus in One Variable 1	6MA041	7.5
Statistics for Engineers	5MS069	7.5
Calculus in One Variable 2	5MA011	7.5
Calculus in One Variable 2	6MA046	7.5
Engineering Physics		
Methods and Tools for Engineers	5FY137	7.5
Linear Algebra	5MA160	7.5
Introductory Course in Engineering Physics	5FY206	7.5
Introductory programming in C and Matlab	5DV157	7.5
Multivariable Calculus	5MA144	7.5
Multivariable Calculus	5MA164	7.5
One-dimensional calculus 1	5MA153	7.5
Classical Mechanics	5FY041	9
One-dimensional calculus 2	5MA154	7.5
Statistics for Engineering Physicists	5MS043	6
Statistics for Engineering Physicists	5MS068	6
Industrial Engineering		

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Table 9: Course Specification for university programmes (Continued)

Introduction to Industrial Engineering and Management	5MA087	7.5
Introduction to marketing and organisation	2FE158	7.5
Introduction to Industrial Engineering and Management	5MA117	7.5
Introduction to Industrial Engineering and Management	5MA195	7.5
Introductory programming in Python and Matlab	5DV105	7.5
Economic Theory and Industrial Organisation	2NE052	7.5
Introductory programming in Python and Matlab	5DV176	7.5
Calculus in One Variable 1	5MA009	7.5
Linear Algebra	5MA019	7.5
One-dimensional calculus 1	5MA153	7.5
Linear Algebra	5MA160	7.5
Calculus in One Variable 2	5MA011	7.5
Industrial Development and Economic Change	2EH032	7.5
One-dimensional calculus 2	5MA154	7.5
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Industrial Engineering		

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Table 9: Course Specification for university programmes (Continued)

Basic Course in Mathematics	1MA010	5
Single Variable Calculus	1MA013	10
Chemical Principles I	1KB000	10
Scientific Computing I	1TD393	5
Organic Chemistry I	1KB410	10
Biochemistry I	1KB408	5
Linear Algebra and Geometry I	1MA025	5
Inorganic Chemistry I	1KB208	10
Engineering Physics		
Introduction to Engineering Physics	1TE609	5
Several Variable Calculus	1MA016	10
Algebra and Geometry	1MA090	5
Mechanics Basic Course	1FA105	10
Single Variable Calculus	1MA013	10
Electric Measurement Techniques	1TE720	5
Mechanics II	1FA102	5
Applied Mechanics I	1TE760	5
Scientific Computing I	1TD393	5
Electromagnetism I	1FA514	5
Computer Programming I	1TD433	5

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Table 9: Course Specification for university programmes (Continued)

Study Experience	1TN000	1