



DE IMPACT VAN STEM- OPLEIDINGEN TIJDENS HET SECUNDAIR ONDERWIJS OP SCHOOL- EN EERSTE ARBEIDSMARKTUITKOMSTEN

Brecht Neyt



DE IMPACT VAN STEM- OPLEIDINGEN TIJDENS HET SECUNDAIR ONDERWIJS OP SCHOOL- EN EERSTE ARBEIDSMARKTUITKOMSTEN

Brecht Neyt

Promotoren: Dieter Verhaest en Stijn Baert

Research paper SONO/ SONO/2020/1.7/1

Gent, juli 2020

Het Steunpunt Onderwijsonderzoek is een samenwerkingsverband van UGent, KU Leuven, VUB, UA en ArteveldeHogeschool.

Gelieve naar deze publicatie te verwijzen als volgt:

Neyt, B. (2020) De impact van STEM-opleidingen tijdens het secundair onderwijs op school- en eerste arbeidsmarktuitskomsten. Steunpunt Onderwijsonderzoek, Gent

Voor meer informatie over deze publicatie Brecht.Neyt@UGent.be

Deze publicatie kwam tot stand met de steun van de Vlaamse Gemeenschap, Ministerie voor Onderwijs en Vorming.

In deze publicatie wordt de mening van de auteur weergegeven en niet die van de Vlaamse overheid. De Vlaamse overheid is niet aansprakelijk voor het gebruik dat kan worden gemaakt van de opgenomen gegevens.

© 2018 STEUNPUNT ONDERWIJSONDERZOEK

p.a. Coördinatie Steunpunt Onderwijsonderzoek
UGent - Vakgroep Onderwijskunde
Henri Dunantlaan 2, BE 9000 Gent

Deze publicatie is ook beschikbaar via www.steunpuntsono.be

VOORWOORD

In deze studie wordt onderzocht wat de impact is van STEM-opleidingen tijdens het secundair onderwijs op school- en eerste arbeidsmarkttuitkomsten. Deze studie draagt op drie verschillende manieren bij aan de bestaande literatuur rond dit thema. Ten eerste is deze studie één van de eerste waarin de impact van STEM-opleidingen tijdens het secundair onderwijs op tewerkstellingskansen op een causale manier wordt onderzocht. Inderdaad, de meeste bestaande studies focussen op de impact van STEM-opleidingen op lonen. Ten tweede wordt in deze studie voor de eerste keer in de bestaande literatuur een dynamisch econometrisch model geschat. Aan de hand van dit model wordt gecontroleerd voor eventuele niet-waarneembare verschillen tussen studenten die STEM-opleidingen hebben doorlopen en studenten die niet-STEM-opleidingen hebben doorlopen in het secundair onderwijs. Ten derde is deze studie de eerste waarin een onderscheid wordt gemaakt tussen het directe en het indirecte effect van STEM-opleidingen op latere arbeidsmarkttuitkomsten. Het directe effect is te wijten aan het ‘rechtstreekse’ effect van STEM-opleidingen op latere arbeidsmarkttuitkomsten, terwijl het indirecte effect te wijten is aan het effect van STEM-opleidingen op schooltuitkomsten, die op hun beurt een effect hebben op arbeidsmarkttuitkomsten. Een onderscheid maken tussen het directe en het indirecte effect van STEM-opleidingen is belangrijk, gezien deze studie aantoont dat het volgen van STEM-opleidingen in het secundair onderwijs leidt tot betere schooltuitkomsten, met name minder vertraging, minder afstromen en meer gekwalificeerd uitstromen uit zowel het secundair als het tertiair onderwijs. Met betrekking tot arbeidsmarkttuitkomsten toont deze studie een positief effect aan van STEM-opleidingen op tewerkstellingskansen na schoolverlaten, dat wordt gedreven door zowel het directe, ‘rechtstreekse’ effect van STEM-opleidingen als door het indirecte effect via verbeterde schooltuitkomsten.

INHOUD

Voorwoord	4
Inhoud	5
Beleidssamenvatting	6
Wetenschappelijk artikel	9

BELEIDSSAMENVATTING

In de EU28 was de werkloosheid bij jongeren het afgelopen decennium gemiddeld meer dan dubbel zo hoog als de werkloosheid bij niet-jongeren. Dit was *a fortiori* het geval in België. Inderdaad, waar de verhouding tussen de werkloosheid bij jongeren en bij niet-jongeren in de EU28 gemiddeld 2.4 was voor de periode 2010–2016, was dit in België 3.0. Hoewel in Vlaanderen de absolute werkloosheid bij zowel jongeren als bij niet-jongeren lager is dan de Belgische gemiddelden, is de ratio tussen deze twee indicatoren in Vlaanderen 3.6, waarmee het slechter scoort dan de meeste EU28 landen (en veel slechter dan Duitsland dat met een ratio van 1.6 het beste scoort) en daarmee op het niveau van Italië zit.

Ondanks deze hoge relatieve werkloosheid bij jongeren, zijn er toch veel openstaande vacatures voor starterjobs. Deze combinatie van een hoge relatieve jongerenwerkloosheid enerzijds en veel openstaande vacatures voor starterjobs anderzijds geeft aan dat onderwijs beter kan afgestemd worden op de noden van de arbeidsmarkt. Een mogelijke manier om dit te doen is het promoten van STEM-opleidingen, waar STEM kort is voor ‘Science’, ‘Technology’, ‘Engineering’, en ‘Mathematics’, exacte opleidingen dus. Inderdaad, veel vacatures voor starterjobs zijn op zoek naar afgestudeerden in het vakgebied STEM. Veel van deze vacatures worden door de VDAB zelfs omschreven als ‘knelpuntvacatures’, wat betekent dat ze al langer dan 90 dagen openstaan of dat ze terug ingetrokken werden omdat er geen gepaste kandidaat voor de job kon worden gevonden.

In deze studie onderzoeken we de impact van STEM-opleidingen in het secundair onderwijs op de overgang die jongeren maken van school naar de arbeidsmarkt. Eerdere studies hebben voornamelijk de impact van STEM-opleidingen op latere lonen onderzocht, waardoor de impact van STEM-opleidingen op tewerkstellingskansen onderbelicht is gebleven. Hoewel Laurijssen en Glorieux (2018) de impact van STEM-opleidingen op tewerkstellingskansen onderzochten in de Vlaamse context, is het onzeker of hun resultaten als causaal geïnterpreteerd kunnen worden. De eerste manier waarop deze studie bijdraagt aan de bestaande literatuur is door de *causale* impact van STEM-opleidingen op *tewerkstellingskansen* te gaan onderzoeken. Een tweede manier is door – voor het eerst in de bestaande literatuur – een dynamisch econometrisch model te schatten. De toegevoegde waarde van dit model is dat het controleert voor zowel observeerbare als niet-observeerbare verschillen tussen jongeren die STEM-opleidingen gevolgd hebben en jongeren die niet-STEM opleidingen gevolgd hebben in het secundair onderwijs. De modellering van het

dynamisch model laat ons ook toe om een onderscheid te maken tussen het directe en het indirecte effect van STEM-opleidingen op latere arbeidsmarktuitskomsten. Dit is de derde contributie van deze studie aan de bestaande literatuur. Het directe effect is toe te schrijven aan het ‘rechtstreekse’ effect van STEM-opleidingen op arbeidsmarktuitskomsten, dus door de kennis en vaardigheden die de student vergaart in deze opleidingen of door het signaaleffect naar potentiële werkgevers van het doorlopen van meer uitdagende opleidingen. Het indirecte effect is toe te schrijven aan het effect van STEM-opleidingen op schooluitskomsten, die op hun beurt een effect kunnen hebben op arbeidsmarktuitskomsten. Dit onderscheid maken is belangrijk, gezien deze studie aantoont dat STEM-opleidingen een substantiële impact hebben op schooluitskomsten in zowel het secundair als het tertiair onderwijs (zie ook de bespreking van de resultaten verder op deze pagina).

In deze studie wordt gebruik gemaakt van de SONAR dataset, die rijke, longitudinale gegevens bevat omtrent de school- en vroege arbeidsmarktcarrière van Vlaamse jongeren. Specifiek worden de jongeren geboren in 1978 en 1980 bestudeerd, goed voor een totaal van 4607 bestudeerde jongeren. Het analyseren van deze longitudinale gegevens heeft tot voordeel dat de volledige school- en vroege arbeidsmarktcarrière van de jongeren in kaart kan gebracht worden. Het gerelateerde nadeel van deze longitudinale gegevens bespreken we op het einde van deze beleidssamenvatting

De analyses tonen ten eerste aan dat het volgen van STEM-opleidingen (in vergelijking met niet-STEM-opleidingen) een positieve impact heeft op schooluitskomsten in het secundair onderwijs: studenten in deze opleidingen blijven minder vaak zitten, stromen minder vaak af en hebben een hogere gekwalificeerde uitstroom uit het secundair onderwijs. Studenten die STEM-opleidingen volgen in het ASO (maar niet in het TSO of BSO) vatten ook vaker hogere studies aan en hebben een hogere kans tot gekwalificeerd uitstromen uit dit hoger onderwijs in vergelijking met studenten die niet-STEM opleidingen volgen. Het promoten van STEM-opleidingen is dus een manier voor beleidsmakers om het studierendement in het secundair onderwijs (voor studenten uit alle richtingen) en het studierendement in het tertiair onderwijs (voor studenten uit het ASO) te bevorderen. Onze analyses tonen verder aan dat deze verhoging van het studierendement door het volgen van STEM-opleidingen vooral het geval is voor vrouwelijke studenten en studenten met een migratieachtergrond.

Ten tweede tonen de analyses aan dat STEM-opleidingen in het secundair onderwijs ook aanzienlijke positieve effecten hebben op latere tewerkstellingskansen. Deze positieve effecten zijn zichtbaar reeds drie maanden na schoolverlaten en blijven op zijn minst duren tot vijf jaar na schoolverlaten. Dit positief effect van STEM-opleidingen is te wijten aan zowel het directe effect

als het indirecte effect via de betere schooluitkomsten die studenten realiseren bij het volgen van een STEM-opleiding. Hoewel beschrijvende statistieken aantonen dat vrouwelijke studenten en studenten met een migratieachtergrond minder vaak STEM-opleidingen volgen tijdens het secundair onderwijs, vinden we geen evidentie voor heterogene effecten van STEM-opleidingen op latere tewerkstellingskansen naar gender of naar migratieachtergrond. Zoals verondersteld, kan promoten van STEM-opleidingen in het secundair onderwijs een manier zijn voor beleidsmakers om de overgang van school naar de arbeidsmarkt te verbeteren, dit voor zowel mannelijke als vrouwelijke studenten en voor zowel autochtone als allochtone studenten.

We eindigen deze beleidssamenvatting door op de belangrijkste limitatie van deze studie te wijzen. Deze studie is gebaseerd op individuen die hun middelbare schoolcarrière doorlopen hebben in de jaren negentig, waardoor de analyses uitgevoerd zijn met historische data. Sindsdien zijn er twee belangrijke ontwikkelingen op vlak van STEM. Ten eerste zijn STEM-opleidingen de laatste jaren reeds gepromoot door beleidsmakers. Als gevolg hiervan bevatten de STEM-opleidingen niet meer enkel leerlingen met een bijzonder hoge interesse in STEM. Het hogere studierendement in STEM-opleidingen dat werd aangetoond in deze studie is daarom misschien niet meer aanwezig. In de meest recente 'STEM-monitor' wordt dit lagere studierendement aan de hand van beschrijvende statistieken al aangetoond. Ten tweede is de impact van STEM in de (Vlaamse) economie bijzonder sterk toegenomen sinds de millenniumwisseling. Als gevolg hiervan kunnen de gevonden effecten omtrent de impact van het volgen van STEM-opleidingen op arbeidsmarktkansen potentieel een onderschatting zijn.

WETENSCHAPPELIJK ARTIKEL

Vanaf volgende pagina.

THE IMPACT OF STEM PROGRAMMES ON SCHOOLING AND EARLY LABOUR MARKET OUTCOMES

Brecht Neytⁱ

Abstract

In this study I examine the impact of being enrolled in STEM programmes during secondary education on schooling and early labour market outcomes. To control for unobservable differences between students in and out of STEM programmes, I use rich longitudinal data from Belgium to estimate a dynamic discrete choice model in which I jointly estimate the schooling and early labour market careers of youths. I find no evidence that students enrolled in STEM programmes differ substantially from students enrolled in non-STEM programmes based on unobservable characteristics. Concerning schooling outcomes, I find that enrolment in STEM programmes reduces study delay and track downgrading and increases graduating from secondary and tertiary education. With respect to labour market outcomes, I find that students enrolled in STEM programmes during secondary education are more often employed after leaving school, especially so with a permanent contract.

Keywords: STEM; education; labour.

JEL codes: I21; I26; J21; J24.

ⁱ **Corresponding author.** Ghent University, Sint-Pietersplein 6, 9000 Ghent, Belgium. Brecht.Neyt@UGent.be. +32499164992.

1 Introduction

Youth unemployment rates substantially exceed non-youth unemployment rates in the EU28. Indeed, Figure 1 clearly indicates that over the past decade, youths are substantially more often unemployed than non-youths and that this is *a fortiori* the case in Belgium.¹ Additionally, Table 1 shows that the ratio between the youth and non-youth unemployment rate (hereafter: “relative youth unemployment rate”) is especially problematic in Flanders, which is the region I analyse in this study. Despite this high relative youth unemployment rate, many employers – again both in the EU28 in general and in Belgium and Flanders in particular – do not find suitable candidates for many (entry-level) vacancies (Cappelli, 2014; OECD, 2020; VDAB, 2020). Consequently, this co-existence of on the one hand a high relative youth unemployment rate and on the other hand many unfilled (entry-level) vacancies indicates that youths are not adequately pointed to education programmes that would provide them with a job after leaving school.

< Figure 1 about here >

< Table 1 about here >

Pointing youths to STEM programmes – ‘STEM’ being short for Science, Technology, Engineering, and Mathematics – may improve their school to work transition for two reasons. First, labour demand for graduates from STEM fields substantially exceeds labour supply. Indeed, a substantial amount of the unfilled vacancies discussed in the previous paragraph are for candidates educated in STEM fields (VDAB, 2012; Cappelli, 2014; Chevalier, 2017). Moreover, these vacancies in STEM fields often reach the status of so-called ‘bottleneck vacancies’, which means that these vacancies are open for longer than 90 days or that they were even cancelled because no suitable candidate could be found (VDAB, 2012).

Second, the demand for graduates with expertise in STEM fields is only bound to increase, as the economy in the EU28 is increasingly fuelled by technological innovation which increasingly requires such expertise in STEM fields (Black, He, Muller, & Spitz-Oener, 2015; Chachashvili-Bolotin, Milner-Bolotin, & Lissitsa, 2016; Bozick, Srinivasan, & Gottfried, 2017). Additionally, Grinis (2019) noted that employers hiring for non-STEM occupations are also increasingly looking for graduates from STEM fields, as also in non-STEM occupations STEM skills such as statistics and software development have become more and more important. As a result, many STEM graduates do indeed work in non-STEM occupations (Chevalier, 2017; Grinis, 2019).

¹ The definition for ‘youth’ (‘non-youth’) in this figure is defined as individuals between 16 and 24 years old (individuals between 25 and 64 years old).

Promoting STEM education to smooth youths' transition from school to the labour market – for example by providing them with information on the labour market opportunities in both STEM field and non-STEM fields – may particularly be interesting for girls, as they are to date substantially underrepresented in STEM fields (Card & Payne, 2017; Justman & Méndez, 2018; Delaney & Devereux, 2019). This is also apparent from the summary statistics of the data used in this study (*infra*, Subsection 3.2). Different studies point to different potential explanations for this gender gap. On the one hand, multiple studies have suggested that the gender gap in STEM education is due to boys' comparative advantage in STEM subjects over non-STEM subjects compared to girls (see Delaney and Devereux (2019) for a recent review of this literature). On the other hand, Miller, Nolla, Eagly, and Uttal (2018) suggest that the gender gap in STEM education is due to gender stereotypes attached to STEM education and STEM jobs. Indeed, in an experiment where they let children draw a scientist, most children drew a man, suggesting that STEM education and STEM jobs would be more suitable for men, leading to less enrolment in STEM education by girls. Promoting STEM education for girls may substantially improve their chances of securing a job after leaving school, as well as provide part of the solution to counter unfilled vacancies in STEM fields. Additionally, addressing the gender gap in STEM education may prove important to address the gender gap in earnings, as Card and Payne (2017) suggest that in the U.S. and Canada the gender gap in STEM education explains about 20% of the gender gap in earnings.

Similarly, also racial minorities are underrepresented in STEM education (Griffith, 2010). Again, this also shows up in the summary statistics of the data used in this study, with students with a migration background being less often enrolled in STEM programmes (*infra*, Subsection 3.2). Promoting STEM education among students with a migration background may again provide part of the solution to counter unfilled vacancies in STEM fields as well as increase foreign youths' chances of a smooth transition from school to a job. This is especially true since vacancies in STEM fields are difficult to fill (*supra*) and Baert, Cockx, Gheyle, and Vandamme (2013) have shown that ethnic discrimination is non-existent in such bottleneck vacancies, whereas they did find evidence for ethnic discrimination in non-bottleneck vacancies.

As previously pointed out by Bozick et al. (2017), existing research on the impact of STEM education has left its impact on the transition from school to work underexposed. Indeed, previous literature has mainly focussed on its impact on later earnings. More specifically, looking at STEM education during secondary education, Jain, Mukhopadhyay, Prakash, and Rakesh (2018) showed (using data from India) that studying science (compared to business and humanities) in high school resulted in higher earnings later in the career. Next, Black et al. (2015) found that U.S. students who took upper level math and science courses in high school had higher wages during their professional career. Similarly, again using

U.S. data, Rose and Betts (2004) found that more advanced math courses in high school led to higher earnings ten years later. Looking at STEM education during tertiary education, Hastings, Neilson, and Zimmerman (2013) and Kirkebøen, Leuven, and Mogstad (2016) report higher wages for students with (health) science majors using Chilean and Norwegian data, respectively. Additionally, Chevalier (2017) (using U.K. data) and Kinsler and Pavan (2015) (using U.S. data) also found evidence for higher wages for science majors, but only if the graduates were employed in science fields. Contrarily, Bozick et al. (2017) found no evidence that non-college bound youths who took advanced academic or applied STEM courses in high school earned higher wages immediately after leaving school. As a first contribution to the existing literature on STEM education, I examine the impact of STEM education in secondary education not on later earnings but on employability, i.e. on the probability of finding a (permanent) job after leaving school. With respect to employability, Bozick et al. (2017) have shown that STEM education in high school does not lead to higher employability in the STEM economy.

Additionally, there are two other ways in which I contribute to the existing research on STEM education. As a second contribution, I examine the impact of a student's decision to do a STEM programme also on schooling outcomes in secondary and tertiary education. Consequently, I am also able to make the distinction between the direct and indirect effect of STEM programmes on employment outcomes. On the one hand, the direct effect of STEM programmes is due to the impact of STEM programmes *per se* on individuals' employability because of the skills and knowledge acquired in STEM programmes itself or because of the signal to employers of enrolling in what is perceived as more challenging programmes. On the other hand, the indirect effect is due to the impact of STEM programmes on schooling outcomes, which in turn may impact one's employability. In existing literature, only the direct effect of STEM programmes on employability is examined, i.e. the effect while keeping schooling outcomes fixed.

The third contribution of this study to the existing literature on STEM education is by using a methodology that has not yet been used in this literature to try to control for a potential selection bias. Indeed, the findings of existing studies may be biased due to these studies not controlling for unobservable differences between students in STEM programmes and students in non-STEM programmes. This may cause that the apparent impact of being enrolled in STEM programmes may be driven by – for example – students in STEM programmes being more ambitious or more motivated than their counterparts in non-STEM programmes. In this study I estimate a dynamic discrete choice model using unique longitudinal data from Flanders, which allows to control for unobservable differences between students in and out of STEM programmes, based on assumptions discussed in detail in Section 4.

The remainder of this study is structured as follows. In the next section, I sketch the institutional setting in Flanders, which is the region from which I analyse data. These data are presented in Section 3. In Section 4 I discuss in detail the dynamic discrete choice model which I use to analyse the data. Section 5 presents the results of my estimations and Section 6 summarises, provides insights for policy makers, and points out several limitations of this study and related avenues for future research.

2 Institutional setting

2.1 Flemish education system

In this study I examine schooling and early labour market careers of Flemish youths. A schematic overview of the education system in Flanders can be found in Figure 2. In Flanders, there is compulsory education from September 1st of the year in which a child reaches age 6. However, before the start of compulsory education almost all children (98.6% in the school year 2016–2017) already attend pre-school education from age 2.5 on. Compulsory education ends on June 30th of the year in which a child reaches age 18 or their 18th birthday, whichever comes first. Compulsory education in Flanders is split up in two periods: primary education and secondary education. After that, individuals who want to pursue further education can enrol in tertiary education.

< Figure 2 about here >

So, after voluntarily attending pre-school education, a child goes through six years of primary education, which she/he usually starts at age 6. However, entry can be delayed if the child does not meet pre-defined standards to be allowed to start primary education. Similarly, succession to higher years in primary education can be delayed if a child does not meet pre-defined standards at the end of a certain school year. The child is then required to repeat that school year. There is no tracking in primary education.

Then, after successfully completing primary education youths enrol in secondary education. Secondary education consists of six or seven school years (*infra*), which a student starts at age 12 if she/he was not delayed before or during primary education. Again, also during secondary education students can be delayed if they do not meet pre-defined standards at the end of a certain school year. The student is then required to repeat that school year. Secondary education is characterised by tracking. In the first two years of secondary education there are two tracks: the general track and the vocational track. From the third year on, there are four tracks, summed up from 'highest' to 'lowest'

these are the general track; the technical track and the arts track (on the same 'level'); and the vocational track. Students in the general track, the technical track, and the arts track go through six years of secondary education, while this extends to seven years for students in the vocational track.² At the end of each school year, students can downgrade from one track to a lower track. Although in theory students are also allowed to upgrade (going from one track to a higher track), this does not happen in practice. From age 15 onwards, students can decide to enrol in part-time vocational education. In these programmes, students go to school for one or two days a week, while for the remaining days they are employed as an apprentice with an employer.

A final period in Flemish youths' schooling careers is – voluntary – tertiary education. Students who successfully completed full-time school-based secondary education – i.e. they did not only complete part-time vocational education mentioned in the previous paragraph – are unconditionally allowed to start any type of higher education. The only exception is for students who want to study medicine and dentistry, who have to successfully complete an entry exam. Tertiary education usually comprises three years (short cycle) or four to five years (long cycle) of schooling. However, some long cycles comprise more than five years of schooling, such as for students who want to study medicine: they study for seven years.

2.2 STEM programmes

Between 2012 and 2020, one of the goals of the Flemish government was to promote STEM education among Flemish youths, both in secondary and tertiary education. Their actions and objectives were written down in the 'STEM action plan 2012–2020'. To monitor enrolment in STEM programmes, in this 'STEM action plan 2012–2020' the Flemish government – in particular the Department of Education and Training – sorted each programme offered by Flemish education institutions in one of four categories based on their STEM content. These categories were defined as follows:

- STEM programmes: programmes which are clearly dominated by STEM courses.
- Light-STEM programmes: programmes with a substantial amount of STEM courses, but which are less dominant in the programmes compared to STEM programmes.
- Healthcare-STEM programmes: programmes with a substantial amount of STEM courses aimed at the healthcare sector.
- Non-STEM programmes: all other programmes by exclusion.

² Although it is not the default option, also students in the non-vocational tracks can enrol in a seventh school year. This is also considered as part of the secondary education career (instead of the tertiary education career).

For programmes in secondary education, a distinction between these four categories of programmes with respect to their STEM content could be made from the third year of secondary education on. I use the abovementioned distinction made by the Flemish government as basis for the distinction between STEM programmes and non-STEM programmes in this study. More specifically, in this study I make a distinction between on the one hand STEM programmes and on the other hand all other programmes, which are hereafter referred to as non-STEM programmes. This means that also light-STEM programmes and healthcare-STEM programmes are defined in this study as non-STEM programmes. This is not an issue, as in secondary education only about 40 students each school year were enrolled in light-STEM programmes and 0 students were enrolled in healthcare-STEM programmes.³ In this study a student is considered as having ‘STEM treatment’ during secondary education if she/he has been enrolled in STEM programmes for three or more school years during secondary education.

For programmes in tertiary education, the distinction between the four categories of programmes with respect to their STEM content is more relevant, as a more substantial amount of students enrol in light-STEM programmes (73 students) and healthcare-STEM programmes (288 students). Here too, in this study these programmes are considered as ‘non-STEM programmes’.

3 Data

3.1 Sample

For this study I make use of the SONAR dataset, which contains rich longitudinal data on Flemish youths’ schooling and early labour market careers as well as many background characteristics of these youths. I analyse data from two cohorts: youths born in 1978 and 1980. To be able to analyse a homogeneous group of individuals, I deleted individuals who started primary education with already more than one year of study delay (22 individuals), had special needs and were therefore in schools that provided special care (97 individuals), enrolled in part-time vocational education (406 individuals), and enrolled in the arts track – which is chosen by only few students (123 individuals). Additionally, I deleted data from individuals who started a PhD, as it is ambiguous whether these individuals should be counted as students or employees during their PhD years (49 individuals). To be able to model year-by-year transitions in students’ schooling careers, I deleted individuals who already dropped out in the fourth

³ More specifically, 40, 32, 48, 47, and 12 students were enrolled in light-STEM programmes in the third, fourth, fifth, sixth, and seventh year of secondary education, respectively.

or fifth year of secondary education (173 individuals). This was possible for individuals who already had two or one years of study delay by then. Finally, I deleted individuals with inconsistent or obvious erroneous data (523 individuals). This led to a final sample size of 4,607 individuals.

3.2 Exogenous variables

In the econometric model (*infra*, Subsection 4.1) I include six strictly exogenous variables as control variables: students' (i) gender, (ii) migration background, (iii) number of siblings, (iv and v) maternal and paternal education level, and (vi) day of birth within the calendar year. Summary statistics of these exogenous variables can be found in Panel A of Table 2. In this table, I also make a comparison between students enrolled in STEM programmes for three or more years during secondary education (the STEM treatment, *supra*, Subsection 2.2) (columns 3 and 4) and students not enrolled in STEM programmes for three or more years (columns 5 and 6). In line with existing literature (*supra*, Section 1), females significantly less often enrol in STEM programmes than males. Indeed, while the proportion of females in the sample enrolled in STEM programmes is 31.7%, it is more than twice as high (69.2%) in the sample not enrolled in STEM programmes. Additionally, students in STEM programmes have slightly higher educated parents and slightly less often have a migration background, the latter which is also in line with existing literature (again, *supra*, Section 1).

< Table 2 about here >

Additionally, as a final exogenous variable the regional unemployment rate at the moment of each of the endogenously modelled outcomes (*infra*, Subsection 3.3) is included in the estimations. This way, I aim to control for both the time-varying and the location-varying economic environment.

3.3 Endogenous variables

In the dynamic discrete choice model (*infra*, Subsection 4.1), I jointly estimate 25 schooling and early labour market outcomes. Below, I discuss these endogenous variables by the four periods in which they occur, i.e. (i) primary education, (ii) secondary education, (iii) tertiary education, and (iv) early labour market.

First, in primary education, I model students' study delay at the start of this schooling period and their additional study delay at the end of this schooling period. Second, in secondary education, I also model year-by-year additional study delay. Additionally, I model students' track choice by estimating their track choice in the first and third school year of secondary education and whether they downgrade in the other school years. Next, from the third year on, I model whether students choose to enrol in a

STEM programme. As a final outcome in secondary education, I model whether students obtain a secondary education qualification. Third, in tertiary education, I model whether students start this form of higher education, and if they do whether they enrol in a STEM programme. Here too, I estimate whether students successfully complete this schooling period, i.e. whether they obtain a tertiary education qualification. Fourth, I model two groups of early labour market outcomes. As a first group, I model whether students are employed three months, one year, and five years after leaving school. As a second group, I estimate – in an analogous, parallel model – whether students are employed with a *permanent* contract also three months, one year, and five years after leaving school.

Panel B of Table 2 shows summary statistics of the endogenous variables. Here too I make a first comparison between students with STEM treatment (columns 3 and 4) and students without STEM treatment (columns 5 and 6). With respect to the schooling outcomes of interest, students in STEM programmes during secondary education less often have study delay and are in higher tracks. However, they do not appear to substantially more often obtain a secondary education qualification. Additionally, students in STEM programmes more often start tertiary education and especially tertiary education in STEM programmes. Next, they also substantially more often graduate from tertiary education. With respect to the labour market outcomes of interest, students in STEM programmes during secondary education more often have a job three months, one year, and five years after leaving school. This effect is even stronger when looking at the labour market outcomes ‘permanent contract after leaving school’.

4 Method

In this section, I present the econometric model used to estimate the impact of STEM programmes during secondary education on schooling and early labour market outcomes. The contribution of the model is twofold. First, it allows us to explicitly control for unobservable differences between students in STEM programmes and students in non-STEM programmes. Second, it allows us to make a distinction between the direct effect of STEM programmes (conditional on altered schooling outcomes) and its indirect effect (through altered schooling outcomes).

4.1 Econometric specification

More specifically, I estimate a dynamic discrete choice model in which I model sequential outcomes in students’ secondary and tertiary schooling career and early labour market career. In presenting the model in this subsection, for the early labour market outcomes I use the labour market outcomes

‘employed after leaving school’. For the labour market outcomes ‘permanent contract after leaving school’ the modelling is analogous. Figure 3 gives a schematic overview of all modelled outcomes. See Subsection 3.3 for a discussion of these endogenous variables.

< Figure 3 about here >

The choice set for a specific outcome, denoted by C^O , is a set of binary or ordinal numbers: $C^O = \{0, 1, \dots, n^O\}$, where n^O defines the number of choices that can be made for outcome O minus 1. The outcomes ‘(additional) study delay’ are all ordinal outcomes representing the number of (additional) years a student is behind compared to when this student would not have been delayed. The outcomes ‘track choice’ and ‘downgrade’ are binary for the first two years of secondary education because in these two years students are either in the general track or in the vocational track (*supra*, Subsection 2.1). The outcomes ‘track choice’ and ‘downgrade’ are ordinal from the third year of secondary education onwards because from then on students can be in the general track, the technical track, or the vocational track. A one-step downgrade means a downgrade from the general track to the technical track or from the technical track to the vocational track; a two-step downgrade means a downgrade from the general track to the vocational track. The outcomes ‘STEM programme’ are binary, i.e. ‘0’ if a student enrolled in a non-STEM programme and ‘1’ if a student enrolled in a STEM programme. Only for the outcome ‘STEM programme end secondary education’ it is ordinal and can take on the values ‘0’, ‘1’, or ‘2’. More specifically, this outcome can have the value ‘2’ only for students in the vocational track if they do their sixth and seventh school year (*supra*, Subsection 2.1) in a STEM programme. Finally, the outcome ‘secondary education qualification obtained’ and all outcomes in tertiary education and the early labour market outcomes are binary.

The outcomes ‘downgrade’ are not modelled for students in the vocational track, as these students are unable to immediately change tracks – they would have to repeat at least one school year. Similarly, the outcomes ‘tertiary education STEM enrolment’ and ‘tertiary education qualification’ are only modelled for students who start tertiary education.

The optimal choice \hat{c}_i^O of an individual i with respect to outcome O is the following:

$$\hat{c}_i^O = c \in C^O \quad \text{if} \quad \omega_c^O < U_{i,c}^O \leq \omega_{c+1}^O$$

where $U_{i,c}^O$ is the latent utility of choice c for outcome O , and ω_c^O and ω_{c+1}^O are threshold utilities (‘cut-off values’) that determine the ordered choice ($\omega_0^O \equiv -\infty$ and $\omega_{n^O+1}^O \equiv +\infty$). In line with the literature, I approximate this $U_{i,c}^O$ by a linear index:

$$U_{i,c}^O = Z_i \alpha^O + R_i^O \beta^O + V_i^O \gamma^O + v_{i,c}^O.$$

In this equation, Z_i is a vector representing the exogenous variables as observed for individual i , and R_i^O captures the regional unemployment rate at the moment of outcome O , both of which are described in Subsection 3.2. To reduce the number of parameters estimated – and therefore to prevent overfitting of the model – I impose that the exogenous variables Z_i and R_i^O have the same impact on outcomes in *the same category*. More specifically, the exogenous variables impact all outcomes related to the categories study delay; track choice and downgrade; STEM programme; and labour market outcomes in the same way. This way, only 4 (number of categories) \times 7 (number of exogenous variables) = 28 parameters needed to be estimated for the first 18 and last 3 outcomes, instead of 21 (number of outcomes) \times 7 (number of exogenous variables) = 147. Doing this did not substantially worsen the goodness of fit of the model (*infra*, Subsection 4.4). Next, V_i^O is the vector of endogenous outcomes that are realised before outcome O , which are described in Subsection 3.3. If an endogenous variable acts as an explanatory variable, the aggregate of all variables in the same category are used. For example, if the endogenous variable ‘study delay’ is used as explanatory variable, it is the aggregated study delay indicating the total number of years of delay at the moment of outcome O .

The vectors α^O , β^O , and γ^O are vectors of associated parameters and $v_{i,c}^O$ is unobservable from the researcher’s point of view. I follow Cameron and Heckman (2001) by assuming that $v_{i,c}^O$ is characterised by the following structure:

$$v_{i,c}^O = \delta_k^O \eta + \varepsilon_{i,c}^O,$$

in which η is a random effect, independent of $\varepsilon_{i,c}^O$, and independent across individual students, which captures unobserved determinants of the outcomes in the model. Here too, I impose that a random effect impacts outcome variables in the same category in the same way. The error term $\varepsilon_{i,c}^O$ is i.i.d. and assumed to be logistically distributed.

As a consequence, I can write the probability of a particular outcome value as:

$$\Pr(\hat{c}_i^O = c | Z_i, R_i^O, V_i^O, \eta_k; \vartheta) = \frac{\exp(\omega_{c+1}^O - Z_i \alpha^O - R_i^O \beta^O - V_i^O \gamma^O - \delta_k^O \eta - \varepsilon_{i,c}^O)}{1 + \exp(\omega_{c+1}^O - Z_i \alpha^O - R_i^O \beta^O - V_i^O \gamma^O - \delta_k^O \eta - \varepsilon_{i,c}^O)} - \frac{\exp(\omega_c^O - Z_i \alpha^O - R_i^O \beta^O - V_i^O \gamma^O - \delta_k^O \eta - \varepsilon_{i,c}^O)}{1 + \exp(\omega_c^O - Z_i \alpha^O - R_i^O \beta^O - V_i^O \gamma^O - \delta_k^O \eta - \varepsilon_{i,c}^O)}$$

in which I denote the vector of unknown parameters by ϑ . The likelihood contribution $\ell_i(Z_i, R_i^O, V_i^O, \delta_k^O \eta; \vartheta)$ for any sampled individual, conditional on the unobservable η , is then constructed by the product of the probabilities of the choices realised in the data for the 25 modelled outcomes.

Following the literature, I adopt a non-parametric discrete distribution for the unobserved random variable η . I assume that this distribution is characterised by an *a priori* unknown number of K

heterogeneity types to which are assigned probabilities $p_k(q)$ specified as logistic transforms:

$$p_k(q) = \frac{\exp(q_k)}{\sum_{j=1}^K \exp(q_j)} \quad \text{with } k = 1, 2, \dots, K; q \equiv [q_1, q_2, \dots, q_K]' \text{ and } q_1 = 0.$$

As Cameron and Heckman (1998; 2001) show, identification of the random effect is proven if at the start of the model, i.e. delay at the start of primary education, which occurs at age 6, is free of selection. This means that η should be independent of the exogenous variables Z_i and R_i^0 . In contrast with previous studies using this type of model to examine the effect of decisions in education on later employment outcomes, the strength of the model is that it starts very early in the schooling career of the students, i.e. at the start of primary education which occurs at age 6.

4.2 Model selection

Following Gaure, Røed, and Zhang (2007), I use maximum likelihood to estimate the model presented in the previous subsection. To control for unobserved differences between students who choose for STEM programmes and students who do not, I gradually add heterogeneity types to this model. I estimated models with up to eight heterogeneity types. Appendix Table A reports the number of parameters, the log-likelihood, and the Akaike information criterion (AIC) and Bayesian information criterion (BIC) values of models which vary in the number of heterogeneity types K included.

The lowest AIC was obtained for $K = 6$. The lowest BIC was found for $K = 1$. As estimating a model with six heterogeneity types led to multiple heterogeneity types that were rather small in proportion, i.e. 0.2% and 1.6%, 11.4%, and 3.8%, I chose to not use this model as the preferred model. Estimating a model with six heterogeneity types may also result in overfitting due to the high number of parameters that is estimated. Indeed, each additional heterogeneity type implies estimating nine additional parameters, i.e. eight outcome-specific random effects (δ^0) and one probability (q). Still, the estimations of different models consistently identified two heterogeneity types as substantial in proportion and therefore as non-negligible. Therefore, I chose a model with two heterogeneity types as the preferred model. This is in line with existing studies that also chose a model only including heterogeneity types that were substantial in proportion and thereby neglecting information criteria such as AIC and BIC (Belzil & Poinas, 2018; Declercq & Verboven, 2018). Reassuringly, results do not differ substantially between models with one, two, and six heterogeneity types. Coefficient estimates from the models with one and six heterogeneity types are available on request.

The coefficient estimates for the preferred model ($K = 2$) are shown in Appendix Table B.⁴ Unless otherwise stated, the simulations and results discussed below are based on these parameter estimates. The coefficient estimates in Appendix Table B provide further evidence that controlling for unobserved heterogeneity is important. First, as also noted in the previous paragraph, the proportions of the two heterogeneity types are substantial ($p_1 = 41.5\%$, $p_2 = 58.5\%$).⁵ Second, many parameters of the unobserved heterogeneity distributions (δ_k^0) are highly significantly different from 0.

4.3 Simulation strategy

Based on the estimated parameters of the preferred model, I simulate students' schooling outcomes (among which their enrolment in STEM programmes) and early labour market outcomes. To examine the impact of STEM programmes on early labour market outcomes, I run these simulations under different scenarios with respect to students' enrolment in STEM programmes.

The simulation strategy works as follows. First, I randomly draw 999 vectors from the asymptotic normal distribution of the model parameters. Second, in each of the 999 draws, the parameters are used to calculate the probabilities associated with each heterogeneity type. These probabilities are then used to randomly assign a heterogeneity type to each pupil in the sample. Third, based on these randomly drawn parameters and the assignment of individuals to a heterogeneity type, the full sequence of schooling and early labour market outcomes is simulated for each student in the sample. Also this I do for each draw.

More concretely, each outcome is simulated sequentially based on its (ordered) logit specification reported in Subsection 4.1. These specifications yield, for each individual in each draw, a probability for each potential outcome value. These probabilities are then translated to segments on the unit interval. To determine the particular outcome value for each individual in each draw, a random number is generated from the standard uniform distribution. The outcome value assigned to the individual depends on the segment in which this random number falls. Once an outcome is assigned, it is saved and conditioned upon for the subsequent outcomes.

In the sequel, the model prediction of a particular outcome refers to the average of these 999

⁴ For the alternative model with the labour market outcomes 'permanent contract after leaving school', only the coefficient estimates for the labour market outcomes are reported in Appendix Table C. For the other (schooling) outcomes of this alternative model, coefficient estimates are – of course – very similar to the coefficient estimates of the model with the labour market outcomes 'employed after leaving school' in Appendix Table B, so I refer the reader to that table for coefficient estimates on the other (schooling) outcomes.

⁵ Following the equation for $p_k(q)$, $p_2 = \exp(0.344) / (\exp(0) + \exp(0.344))$.

replications. The 95% confidence intervals are constructed by choosing the appropriate percentiles of the 999 simulated probabilities.

4.4 Goodness of fit

To determine how well the preferred model captures the data, for each endogenous variable I compared the actual probability (as observed in the data) with the simulated probability (as estimated by the model). As can be seen from Figure 4 and Appendix Table D, the simulated probabilities are closely distributed around the actual probabilities.⁶ Although the simulated probabilities differ significantly (at the 5% confidence level) from the actual probabilities for the last two labour market outcomes, also here the simulated probabilities (0.881 and 0.949) mirror the actual probabilities very well (0.862 and 0.935). Therefore, I conclude that the model is able to capture the data very well.

< Figure 4 about here >

4.5 Treatment effects

To examine the impact of STEM programmes on early labour market outcomes, I calculate treatment effects. The treatment *in casu* being enrolment in STEM programmes during secondary education.⁷ As mentioned in Subsection 2.2, in this study I define STEM treatment as being enrolled in STEM programmes for three or more years during secondary education.

4.5.1 Average Treatment effects on the Treated (ATTs)

First, I calculate Average Treatment effects on the Treated (ATTs). For the ATTs, the treated are students who – in the simulations (*supra*, Subsection 4.3) – were enrolled in STEM programmes for three or more years during secondary education. For these students, I simulate the *counterfactual* scenario in which they were never enrolled in STEM programmes. Technically, I do this by forcing the variables indicating enrolment in STEM programmes (which were three or more) to zero. Then, I simulate the schooling and early labour market careers of these students in this counterfactual scenario and compare it with their

⁶ For the alternative model with the labour market outcomes ‘permanent contract after leaving school’, only the goodness of fit for the labour market outcomes are reported in Appendix Table D. For the other (schooling) outcomes of this alternative model, the goodness of fit is – of course – very similar to the goodness of fit for the model with the labour market outcomes ‘employed after leaving school’, so I refer the reader to those measures for the goodness of fit of the other (schooling) outcomes.

⁷ Also including the outcome ‘tertiary education enrolment in STEM programme’ as part of the treatment did not substantially change the results. This is because only very few students (5.3%) who have no ‘STEM treatment’ during secondary education enrol in a STEM programme in tertiary education.

factual simulated schooling and early labour market careers. As a result, the ATTs can be presented as follows:

$$ATT = \frac{\text{average outcome across treated individuals}}{\text{average outcome across treated individuals, in the counterfactual of no treatment}}$$

If the ATT is above (below) 1, this means there is a positive (negative) effect of the treatment on the outcome of interest.

4.5.2 Average Treatment effects on the Non-Treated (ATNTs)⁸

Second, I calculate Average Treatment effects on the Non-Treated (ATNTs). For the ATNTs, the non-treated are students who – in the simulations (*supra* Subsection 4.3) – were enrolled in STEM programmes for less than three years during secondary education. For these students, I simulate the counterfactual scenario in which they were enrolled in STEM programmes for four years. Technically, I do this by forcing the four variables indicating enrolment in STEM programmes (which were on aggregate less than three) each to one, for a total of four years in a STEM programme. Then, I simulate the schooling and early labour market careers of these students in this counterfactual scenario and compare it with their factual simulated schooling and early labour market careers. As a result, the ATNTs can be presented as follows:

$$ATNT = \frac{\text{average outcome across untreated individuals, in the counterfactual of treatment}}{\text{average outcome across untreated ind.}}$$

If the ATNT is above (below) 1, this means there is a positive (negative) effect of the treatment on the outcome of interest.

As results from the ATTs and ATNTs are very comparable (as is illustrated in Appendix Table E), in Section 5 I will focus on the results of the ATTs.

4.6 Total, direct, and indirect effects

For all schooling and labour market outcomes realised after the decision to do enrol in a STEM programme, I make a distinction between total effects, direct effects, and indirect effects.

For the total effects, I do not condition the denominator of the equations for the ATTs and the ATNTs on earlier outcomes as would be realised in the scenario of treatment (enrolment in a STEM

⁸ In these analyses both students who were never enrolled in STEM programmes and students who were enrolled in STEM programmes for up to two years are taken together. Consequently, the results from these analyses are more difficult to interpret, so I consider these analyses solely as secondary, robustness analyses.

programme). As a consequence, the treatment impacts the outcomes of interest both directly (via the model's coefficients capturing the direct effect of enrolment in a STEM programme) and indirectly (via the model's coefficients capturing the effect of earlier outcomes, which in turn were (potentially) affected by enrolment in a STEM programme). Therefore, these total effects can also be labelled as 'unconditional effects', i.e. effects without keeping former schooling and labour market outcomes fixed to those of the treatment group.

For the direct effects, in contrast, I do condition the denominators of the equations for the ATTs and the ATNT on earlier outcomes as would be realised in the scenario of treatment (enrolment in a STEM programme). As a consequence, the treatment impacts the outcomes of interest only directly (via the model's coefficients capturing the direct effect of enrolment in a STEM programme). Therefore, these direct effects can also be labelled 'conditional effects', i.e. effects while keeping former schooling and labour market outcomes fixed to those of the treatment group.

The indirect effects are calculated as the average differences between the total effects and the direct effects over all draws of the simulations (*supra*, Subsection 4.3). The indirect effects capture the impact of the treatment through earlier schooling and labour market outcomes (via the model's coefficients capturing the effect of earlier outcomes, which in turn were (potentially) affected by enrolment in a STEM programme).

5 Results

In this section I discuss the results of the analyses. First, I compare the results of the model in which I do not control for unobserved heterogeneity ($K = 1$) with results from the preferred model in which I do control for unobserved heterogeneity ($K = 2$) (*supra*, Subsection 4.2). Second, I compare the direct effect of STEM programmes with their indirect effect through altered schooling outcomes (*supra*, Subsection 4.6). Third, I examine heterogeneous effects of enrolment in STEM programmes by the track in which these STEM programmes were followed. Finally, I examine heterogeneous effects by background characteristics. More specifically, I examine whether results differ between male and female students and between students with and without a migration background.

Table 3 shows the results from both the models without (column 1) and with (column 2) control for unobserved differences between students in STEM programmes and students in non-STEM programmes. In the model with control for unobserved heterogeneity ($K = 2$, column 2), students in STEM programmes obtain a secondary education qualification 4.2% more often than students in non-

STEM programmes. Next, the former students do not significantly more often start tertiary education. However, if students do enrol in tertiary education, students in STEM programmes during secondary education substantially more often enrol in STEM programmes also during tertiary education. Although the ATT of 6.170 for this outcome may seem high in magnitude, this is in line with the summary statistics depicted in Table 2 which also show that students in STEM programmes during secondary education start STEM programmes in tertiary education almost six times more often. Additionally, students with experience in STEM during secondary education have a 15.0% higher probability of successfully completing tertiary education (again conditional on starting it).

< Table 3 about here >

With respect to the labour market outcomes, when looking at the outcomes ‘employed after leaving school’ I find that students with STEM experience during secondary education have 5.1% and 2.8% higher probabilities of having a job one year and five years after leaving school, respectively. Additionally, the effect of STEM programmes during secondary education is even stronger when looking at the outcomes ‘permanent contract after leaving school’. Indeed, already three months after leaving school being enrolled in STEM programmes during secondary education increases the probability of having a permanent contract with 18.5%. This positive effect fades out slowly over time – but remains statistically and economically significant – to 16.9% and 11.9% higher probabilities of having a permanent contract one year and five years after leaving school.

In the model in which I do not control for unobserved heterogeneity ($K = 1$, column 1), results are very comparable to the results of the model in which I do control for unobserved heterogeneity. Apparently, students in STEM programmes and students in non-STEM programmes during secondary education do not substantially differ from each other on characteristics that are unobservable to the researcher. This is in line with earlier findings by Chevalier (2017), who also reported that the self-selection based on unobservable characteristics in STEM programmes and the related bias on employment outcomes is small.

Column (2) and column (3) of Table 4 show respectively the direct and indirect effect of being enrolled in STEM programmes during secondary education. With respect to the outcome ‘secondary education qualification obtained’ it is equally the direct and indirect effect that drives the positive total impact of STEM programmes on this outcome. The positive indirect effect stems from the positive impact of STEM programmes on study delay (less study delay, see Appendix Table B, panels I, L, O, and R) and track choice (less downgrading, see Appendix Table B, panels J, M, and P). A suggestive explanation for this decreased study delay and decreased downgrading is the number of hours of exact courses – such as mathematics – which are to a higher extent offered in the curricula of STEM

programmes. In the existing literature, Cortes, Goodman, and Nomi (2015) indeed show that more hours of math courses increased educational attainment. Next, although STEM programmes have a negative direct effect on enrolment in tertiary education, this is compensated for by a positive indirect effect, again due to better schooling outcomes in secondary education (less study delay, less downgrading, and more graduating from secondary education). Further, the impact of STEM programmes during secondary education on enrolment in STEM programmes in tertiary education is – as expected – completely driven by the direct effect. Next, for the outcome ‘tertiary education qualification obtained’, the positive indirect effect (through better outcomes in secondary education, *supra*) accounts for one third of the total effect.

< Table 4 about here >

With respect to the labour market outcomes ‘employed after leaving school’, there is a positive direct effect three months, one year, and five years after leaving school. For the first employment outcome, this is, however, nullified by a negative indirect effect. This negative indirect effect stems from the favourable impact of STEM programmes during secondary education on the probability that a student downgrades tracks. Consequently, students in STEM programmes less often end up in the ‘lower’ tracks. As being enrolled in these lower tracks at the end of secondary education has – due to the more vocational nature of these tracks – a positive impact on being employed shortly after leaving school, this leads to a negative indirect impact of STEM programmes on the outcome ‘employed three months after leaving school’. For the labour market outcomes ‘permanent contract after leaving school’, there is a positive total effect driven by the indirect effect for the outcomes three months and one year after leaving school and driven by the direct effect for the outcome five years after leaving school. The positive indirect effect for the first two outcomes stems from the beneficial impact of STEM programmes on the probability of starting tertiary education in a STEM programme (panel U of Appendix Table B) and graduating from tertiary education (panel V of Appendix Table B) which both have in turn a positive impact of the first two labour market outcomes (panel W and panel X of Appendix Table C) but no impact on the third (panel Y of Appendix Table C).

A somewhat puzzling result is the negative direct effect of STEM programmes during secondary education on the probability of starting tertiary education. This result can be explained when examining the impact of STEM programmes heterogeneous by track. This is what I do in a first extension of the model. To do this, I introduce interaction terms between enrolment in STEM programmes and the technical and vocational tracks. This way, I can compare the impact of more ‘academic’ STEM programmes (in the general track) and more ‘applied’ STEM programmes (in the technical track and the vocational track). Coefficient estimates for the outcome variables of interest from this extended model

can be found in Table 5. I find that the overall negative impact of STEM programmes during secondary education on tertiary education enrolment is completely driven by students in STEM programmes in the technical and vocational tracks. Indeed, while students enrolled in STEM programmes in the general track more often start tertiary education, students enrolled in STEM programmes in the technical and vocational track less often do so (panel B). This can be explained by the strong pull effect of the labour market that the latter students experience because of their highly requested profiles. An additional finding of this extended model is that enrolment in STEM programmes during secondary education amplifies the trade-off between short term advantages and long-term disadvantages of vocational education. Indeed, while students in the vocational track (and to a certain extent also students in the technical track) have an even higher probability of being employed three months after leaving school when they were enrolled in STEM programmes (panel E), they have an even lower probability of being employed five years after leaving school (panel G).

< Table 5 about here >

Next, I examine heterogeneous effects of STEM programmes by background characteristics of the students. In Table 6, I examine whether the impact of STEM programmes during secondary education differs between male and female students. For this means, I introduce interaction terms between enrolment in STEM programmes during secondary education and the dummy variable for gender. Coefficient estimates for the outcome variables of interest of this extended model can be found in Table 6. The most interesting results can be found for the impact of STEM programmes during secondary education on students' higher education careers. Indeed, while STEM enrolment during secondary education has an overall negative direct effect on the probability of enrolling in tertiary education, the effect for women is positive (Panel B). This finding is to some extent linked to the finding in the previous extended model which shows that STEM programmes have a positive effect on tertiary education enrolment for students in the general track, as women are more often enrolled in STEM programmes in this general track. Additionally, although women already more often graduate from tertiary education, this is even more so if these women were enrolled in a STEM programme during secondary education (Panel D). With respect to the labour market outcomes, no substantial differences between male and female students could be identified with respect to the impact of STEM programmes during secondary education.

< Table 6 about here >

Finally, I examine whether the impact of STEM programmes during secondary education is heterogeneous between students with and students without a migration background. To do this, I again introduce interaction effects, this time between enrolment in STEM programmes during secondary

education and the dummy variable indicating whether an individual has a migration background. Coefficient estimates for the outcome variables of interest from this extended model can be found in Table 7. From these estimates, it is clear that students with a migration background have an increased probability of graduating secondary education (panel A) and starting tertiary education (panel B) if these were enrolled in STEM programmes during secondary education. For the labour market outcomes, again no heterogeneous effects could be found with respect to this background characteristic.

< Table 7 about here >

6 Conclusion

In this study I examined the impact of STEM programmes during secondary education on schooling and early labour market outcomes. With respect to schooling outcomes, I found that enrolment in STEM programmes leads to less study delay, less downgrading, and more graduating from both secondary and tertiary education. These positive effects on graduating are driven by both the direct effect – the impact of STEM programmes *per se* – and the indirect effect – the impact of STEM programmes through improved earlier schooling outcomes. For students in the general track, enrolment in STEM programmes during secondary education also increased the probability that these students start tertiary education, while it did not increase for students in the technical and vocational track. Consequently, by promoting STEM programmes in secondary education, policy makers could increase educational attainment both in secondary education (for students in all tracks) and in tertiary education (for students in the general track).

With respect to labour market outcomes, it was hypothesised that enrolment in STEM programmes during secondary education would improve the transition from school to work given the many unfilled vacancies in the STEM sector (*supra*, Section 1). I indeed found evidence that students enrolled in STEM programmes have better early labour market outcomes compared to youths' enrolled in non-STEM programmes. Here too, the effect is driven both by its direct effect – conditional on improved schooling outcomes – and by its indirect effect – through improved schooling outcomes. Consequently, policy makers should consider promoting STEM education to students already during secondary education to improve their school to work transition.

Whereas it was also hypothesised that STEM education would be especially beneficial for the labour market opportunities of female students and students with a migration background, no evidence could be found in this direction. Indeed, although enrolment in STEM programmes had an especially positive

impact on schooling outcomes for female students and students with a migration background, these students did not benefit more from STEM programmes than their male and native counterparts with respect to labour market outcomes. Still, it is surprising that female students in STEM programmes did not experience lower returns to STEM education compared to males, given the stereotype that STEM jobs would be less suited for women. Additionally, encouraging STEM programmes among these students may be a way for policy makers to substantially improve their educational attainment.

I conclude this study by pointing out two limitations. First, although this study revealed that STEM education has a positive impact on the probability of youths' to find a (permanent) job after leaving school, and therefore that STEM education has the potential of improving the relative youth unemployment rate, it would be interesting to examine whether STEM education may also be a remedy for the youths overeducation entering the labour market, which was found in multiple existing studies (Verhaest, Van Trier, & Sellami, 2011; Verhaest & Van der Velden, 2013). Additionally, although in this study I was able to examine early labour market outcome, due to data constraints I was unable to examine the impact of STEM programmes on labour market outcomes in the (very) long run. Therefore, I would suggest that future research also examines whether the positive impact of STEM programmes on early labour market outcomes is present later in the professional career.

7 References

- Baert, S., Cockx, B., Gheyle, N., & Vandamme, C. (2015). Is there less discrimination in occupations where recruitment is difficult? *ILR Review*, *68*, 467–500.
- Belzil, C., & Poinas, F. (2018). Estimating a model of qualitative and quantitative education choices in France. *Mimeo*.
- Black, S., He, Z., Muller, C., & Spitz-Oener, A. (2015). On the origins of STEM: The role of high school STEM coursework in occupational determination and labour market success in mid-life. *Mimeo*.
- Bozick, R., Srinivasan, S., & Gottfried, M. (2017). Do high school STEM courses prepare non-college bound youth for jobs in the STEM economy? *Education Economics*, *25*, 234–250.
- Cameron, S. V., & Heckman, J. J. (1998). Life cycle schooling and dynamic selection bias: Models and evidence for five cohorts of American males. *Journal of Political Economy*, *106*, 262–333.
- Cameron, S. V., & Heckman, J. J. (2001). The dynamics of educational attainment for Black, Hispanic and White males. *Journal of Political Economy*, *109*, 455–499.
- Cappelli, P. (2014). Skill gaps, skill shortages and skill mismatches: Evidence for the US. *NBER Working Paper Series*, 20382.
- Card, D., & Payne, A. A. (2017). High school choices and the gender gap in STEM. *NBER Working Paper Series*, 23769.
- Chachashvili-Bolotin, S., Milner-Bolotin, M., & Lissitsa, S. (2016). Examination of factors predicting secondary students' interest in tertiary STEM education. *International Journal of Science Education*, *38*, 366–390.
- Chevalier, A. (2017). To be or not to be a scientist? *Mimeo*.
- Cortes, K. E., Goodman, J. S., & Nomi, T. (2015). Intensive math instruction and educational attainment long-run impacts of double-dose algebra. *Journal of Human Resources*, *50*(1), 108–158.
- Declercq, K., & Verboven, F. (2018). Enrollment and degree completion in higher education without admission standards. *Economics of Education Review*, *66*, 223–244.
- Delaney, J. M., & Devereux, P. J. (2019). Understanding gender differences in STEM: Evidence from college applications. *Economics of Education Review*, *72*, 219–238.
- Gaure, S., Røed, K., & Zhang, T. (2007). Time and causality: A Monte Carlo assessment of the timing-of-events approach. *Journal of Econometrics*, *141*, 1159–1195.
- Griffith, A. L. (2010). Persistence of women and minorities in STEM field majors: Is it the school that matters? *Economics of Education Review*, *29*, 911–922.
- Grinis, I. (2019). The STEM requirements of “non-STEM” jobs: Evidence from UK online vacancy postings. *Economics of Education Review*, *70*, 144–158.

- Hastings, J. S., Neilson, C. A., & Zimmerman, S. D. (2013). Are some degrees worth more than others? Evidence from college admission cutoffs in Chile. *NBER Working Paper Series*, 19241.
- Jain, T., Mukhopadhyay, A., Prakash, N., & Rakesh, R. (2018). Labor market effects of high school science majors in a high STEM economy. *IZA Discussion Paper Series*, 11908.
- Justman, M., & Méndez, S. J. (2018). Gendered choices of STEM subjects for matriculation are not driven by prior differences in mathematical achievement. *Economics of Education Review*, 64, 282–297.
- Kinsler, J., & Pavan, R. (2015). The specificity of general human capital: Evidence from college major choice. *Journal of Labor Economics*, 33, 933–972.
- Kirkeboen, L. J., Leuven, E., & Mogstad, M. (2016). Field of study, earnings, and self-selection. *Quarterly Journal of Economics*, 131, 1057–1111.
- Miller, D. I., Nolla, K. M., Eagly, A. H., & Uttal, D. H. (2018). The development of children's gender-science stereotypes: A meta-analysis of 5 decades of US draw-a-scientist studies. *Child development*, 89, 1943–1955.
- Neyt, B., Verhaest, D., & Baert, S. (2018). The impact of dual apprenticeship programs on early labour market outcomes: A dynamic approach. *IZA Discussion Paper Series*, 12011.
- OECD (2019a). Unemployment rate (indicator). doi: 10.1787/997c8750-en (Accessed on 10 September 2019).
- OECD (2019b). Youth unemployment rate (indicator). doi: 10.1787/c3634df7-en (Accessed on 10 September 2019).
- OECD (2020). *Registered Unemployed and Job Vacancies: Job Vacancies*. Retrieved from <https://stats.oecd.org/Index.aspx?QueryId=90602> [accessed on January 30th 2020].
- Rose, H., & Betts, J. R. (2004). The effect of high school courses on earnings. *Review of Economics and Statistics*, 86, 497–513.
- VDAB (2012). *VDAB ontcijfert nr. 27: Knelpuntvacatures overschat?* Brussel: VDAB, Studiedienst.
- VDAB (2020). *Vind een job*. Retrieved from <https://www.vdab.be/vindeenjob/vacatures> [accessed on January 30th 2020].
- Verhaest, D., Van Trier, W., & Sellami, S. (2011). Welke factoren bepalen de aansluiting van onderwijs en beroep? Een onderzoek bij Vlaamse afgestudeerden uit het hoger onderwijs. *Tijdschrift voor Arbeidsvraagstukken*, 27, 415–436.
- Verhaest, D., & Van der Velden, R. (2013). Cross-country differences in graduate overeducation. *European Sociological Review*, 29, 642–653.

8 Appendix

< Appendix Table A about here >

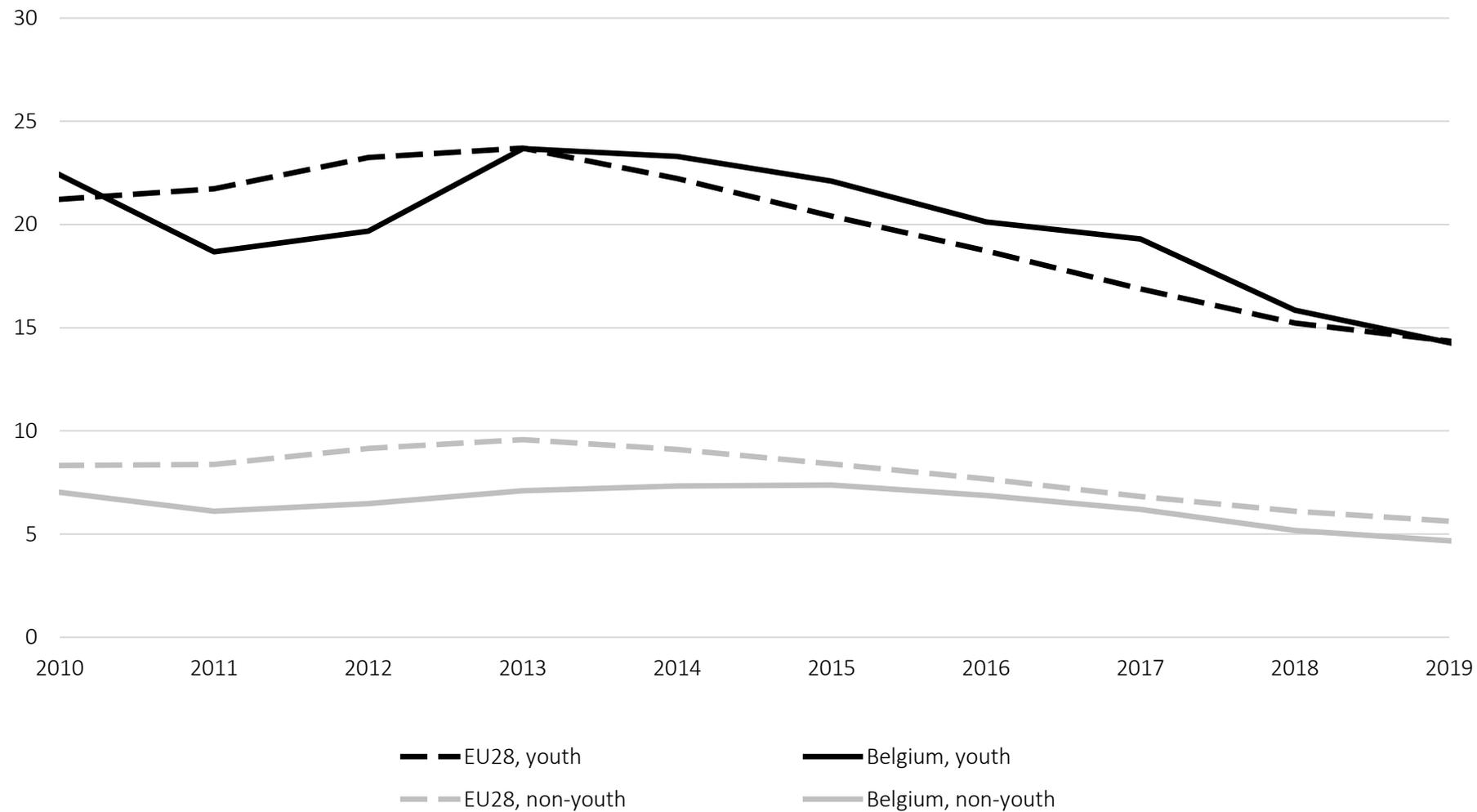
< Appendix Table B about here >

< Appendix Table C about here >

< Appendix Table D about here >

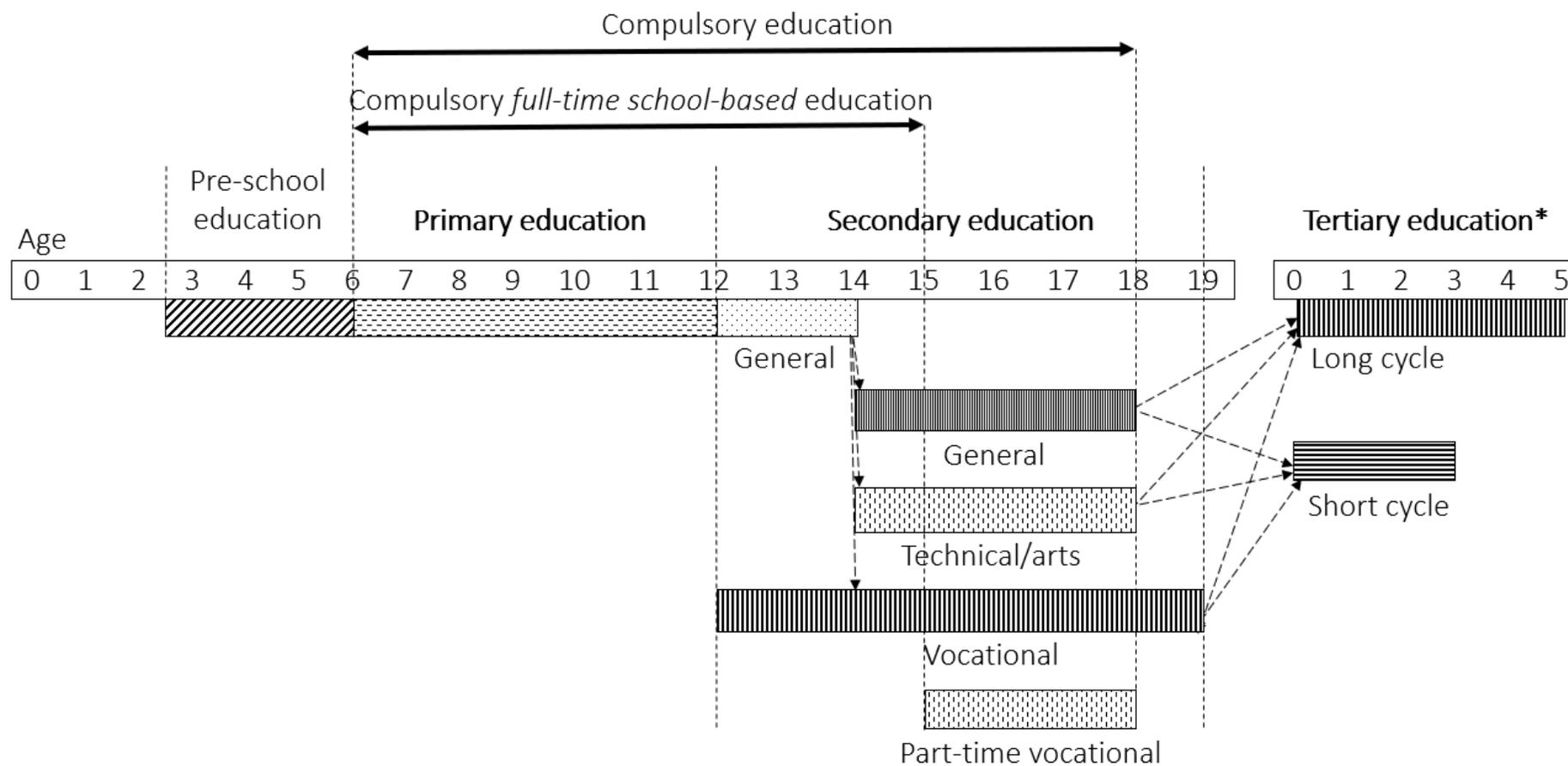
< Appendix Table E about here >

Figure 1. Youth and non-youth unemployment rates in the EU28 and Belgium.



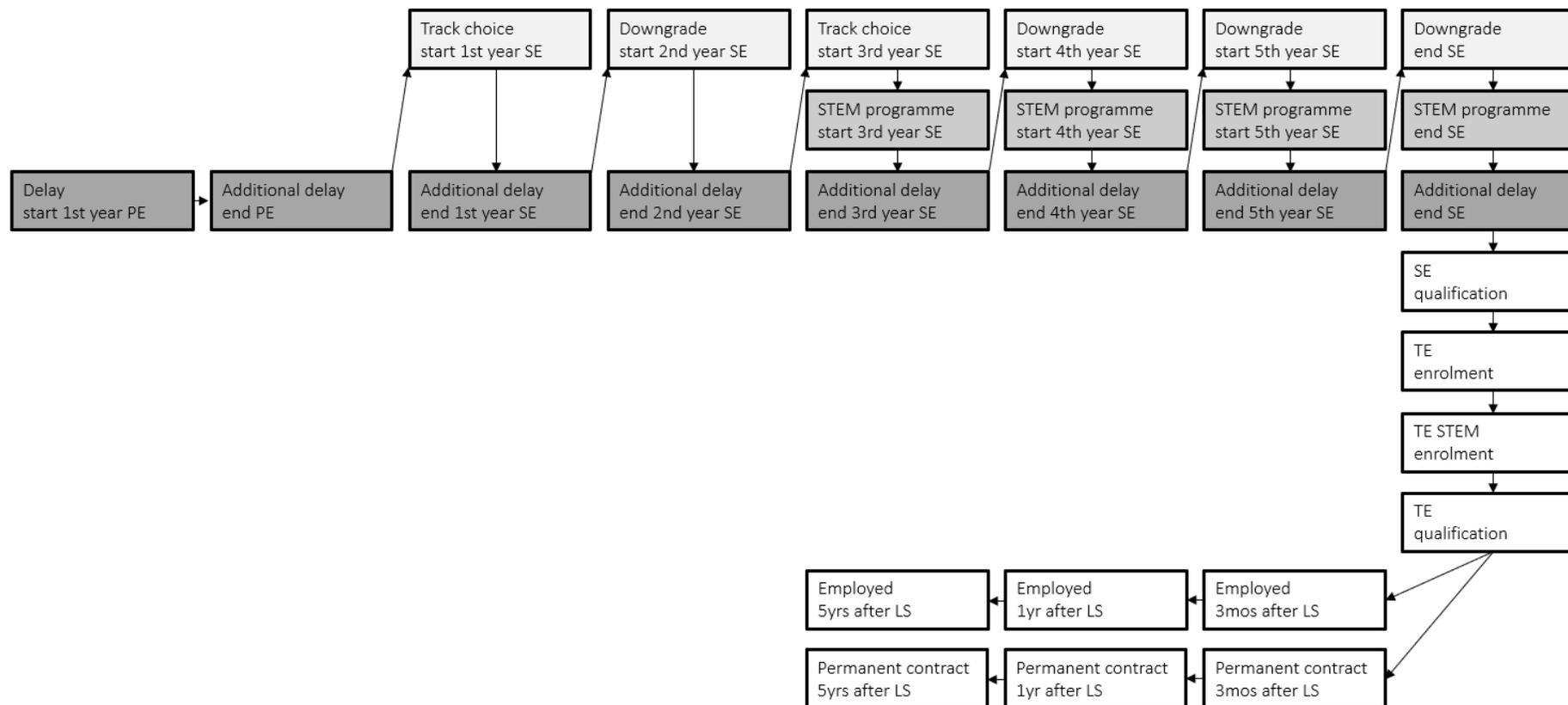
Note. Source: Eurostat. Youth: between 15 and 24 years old. Non-youth: between 25 and 64 years old.

Figure 2. Organisation of education in Flanders.



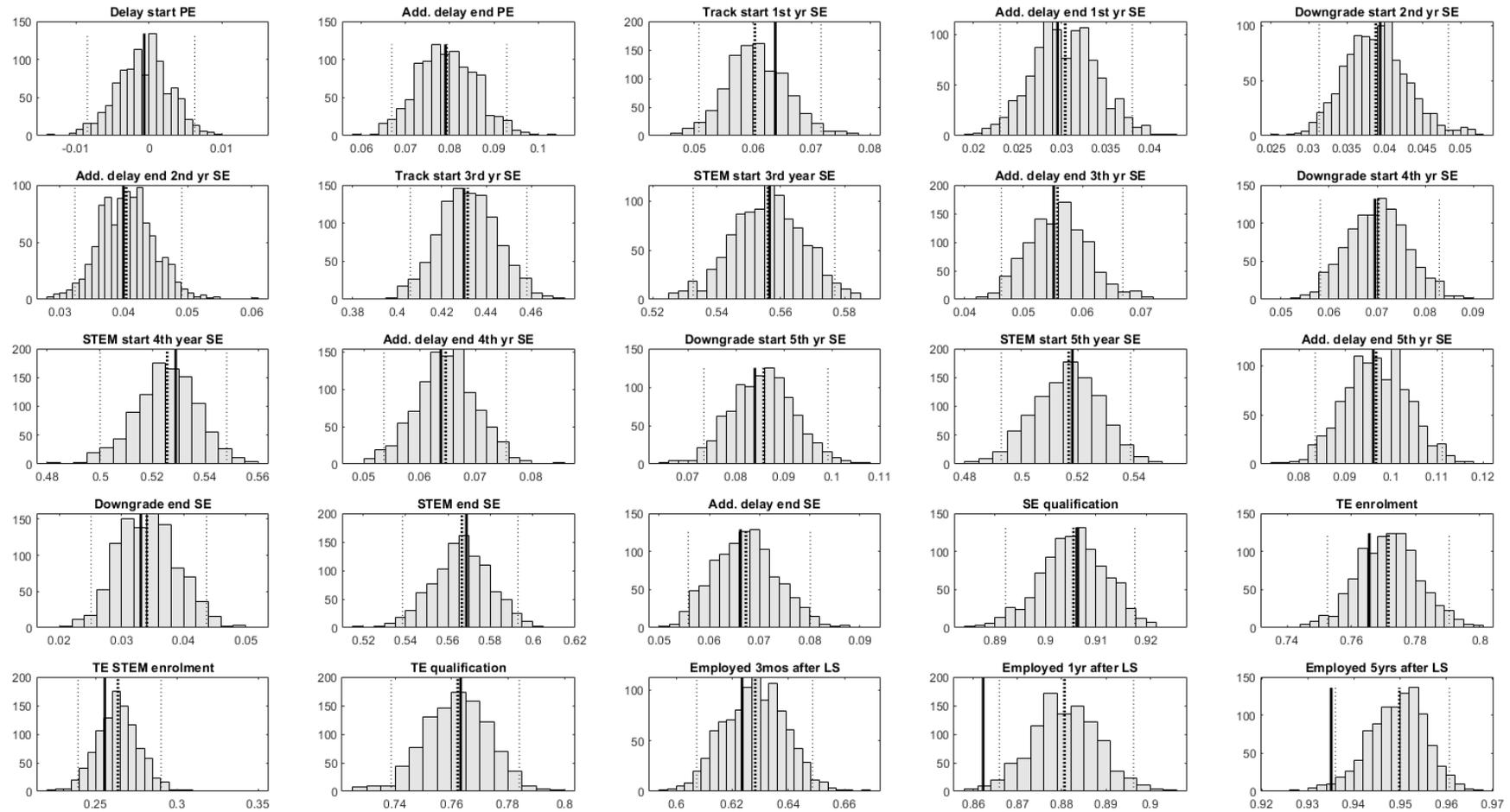
Note. In tertiary education, the timeline indicates the programme duration in years.

Figure 3. Schematic overview of the econometric model.



Note. The following abbreviations are used: PE (Primary Education), SE (Secondary Education), TE (Tertiary Education), mos (months), yr (year), yrs (years), and LS (Leaving School).

Figure 4. Goodness of fit.



Notes. The y-axis indicates how many times (on a total of 999) a particular probability (x-axis) was simulated. The full line indicates the actual probability, the dotted lines indicate the median (thick) and the 95% confidence interval (thin) of the simulated probabilities. The following abbreviations are used: PE (Primary Education), SE (Secondary Education), TE (Tertiary Education), mos (months), yr (year), yrs (years), and LS (Leaving School).

Table 1. Youth and non-youth unemployment rates in the EU28: 2010–2016 average.

Country	15–24 years (1)	25–54 years (2)	Difference: (1) – (2)	Ratio: (1) / (2)
Spain	48.9%	21.1%	27.8%	2.3
Greece	48.7%	21.9%	26.8%	2.2
Italy	36.1%	10.0%	26.1%	3.6
Portugal	32.0%	12.4%	19.6%	2.6
France	23.7%	8.5%	15.2%	2.8
EU28	21.6%	9.0%	12.6%	2.4
Belgium	21.4%	7.2%	14.2%	3.0
Brussels	37.6%	16.9%	20.7%	2.2
Wallonia	29.6%	9.8%	19.8%	3.0
Flanders	14.7%	4.1%	10.6%	3.6
Germany	8.0%	5.0%	3.0%	1.6
Austria	9.9%	4.8%	5.1%	2.1
Netherlands	11.5%	5.0%	6.5%	2.3
Denmark	14.4%	6.2%	8.2%	2.3

Note. Source: Eurostat and Statbel.

Table 2. Summary statistics.

	(1)	(2)	(3)	(4)	(5)	(6)
	I. Whole sample (N = 4,607)		II. Sample enrolled in STEM programmes for three or more years (N = 2,211)		III. Sample not enrolled in STEM programmes for three or more years (N = 2,396)	
	Mean	SD	Mean	SD	Mean	SD
A. Exogenous variables						
Female	0.512	-	0.317	-	0.692	-
Mother's education after primary education (years)	5.580	3.121	5.881	3.088	5.301	3.126
Father's education after primary education (years)	6.003	3.381	6.357	3.362	5.676	3.365
Number of siblings	1.564	1.293	1.520	1.178	1.606	1.391
Migration background	0.049	-	0.037	-	0.060	-
Day of birth within calendar year	181.048	103.305	179.750	102.982	182.246	103.609
B. Endogenous variables						
Primary education						
Delay start 1st year PE	-0.000	0.163	-0.006	0.160	0.005	0.165
Additional delay end PE	0.079	0.303	0.063	0.272	0.093	0.328
Secondary education						
Track choice start 1st year SE	0.063	-	0.052	-	0.074	-
Additional delay end 1st year SE	0.029	0.170	0.025	0.157	0.033	0.181
Downgrade start 2nd year SE	0.036	-	0.038	-	0.035	-
Additional delay end 2nd year SE	0.039	0.201	0.032	0.180	0.046	0.218
Track choice start 3rd year SE	0.588	0.729	0.523	0.706	0.647	0.745
STEM programme start 3rd year SE	0.556	-	0.973	-	0.171	-
Additional delay end 3rd year SE	0.055	0.232	0.047	0.213	0.062	0.249
Downgrade start 4th year SE	0.059	0.242	0.033	0.184	0.083	0.284
STEM programme start 4th year SE	0.528	-	0.978	-	0.113	-
Additional delay end 4th year SE	0.063	0.250	0.046	0.212	0.079	0.280

Table 2. Summary statistics (continued).

Downgrade start 5th year SE	0.069	0.260	0.041	0.199	0.095	0.303
STEM programme start 5th year SE	0.518	-	0.998	-	0.074	-
Additional delay end 5th year SE	0.096	0.313	0.093	0.310	0.098	0.315
Downgrade end SE	0.026	0.169	0.016	0.135	0.035	0.194
STEM programme end SE	0.568	0.597	1.097	0.352	0.080	0.273
Additional delay end SE	0.066	0.285	0.051	0.232	0.080	0.326
Secondary education qualification	0.906	-	0.912	-	0.901	-
Tertiary education						
Tertiary education enrolment	0.693	-	0.717	-	0.671	-
Tertiary education STEM enrolment	0.177	-	0.312	-	0.053	-
Tertiary education qualification	0.529	-	0.593	-	0.470	-
Early labour market						
Employed three months after leaving school	0.623	-	0.639	-	0.608	-
Employed one year after leaving school	0.862	-	0.894	-	0.833	-
Employed five years after leaving school	0.935	-	0.961	-	0.912	-
Permanent contract three months after leaving school	0.314	-	0.345	-	0.285	-
Permanent contract one year after leaving school	0.521	-	0.572	-	0.475	-
Permanent contract five years after leaving school	0.798	-	0.861	-	0.744	-

Note. See Subsection 3.2 and Subsection 3.3 for a description of the mentioned variables. For binary variables no standard deviations are presented.

Table 3. ATTs of STEM programmes on schooling and labour market outcomes: no correction versus correction for unobserved heterogeneity.

	(1)		(2)	
	Total effect ATTs			
	No correction for unobserved heterogeneity (K = 1)		Correction for unobserved heterogeneity (K = 2)	
Secondary education qualification obtained	1.042***	[1.010, 1.074]	1.042***	[1.014, 1.072]
Tertiary education enrolment	0.986	[0.946, 1.032]	0.985	[0.941, 1.033]
Tertiary education enrolment in STEM programme	6.289***	[4.664, 8.300]	6.170***	[4.425, 8.429]
Tertiary education qualification obtained	1.154***	[1.087, 1.226]	1.150***	[1.084, 1.220]
Employed three months after leaving school	1.035	[0.969, 1.106]	1.038	[0.963, 1.113]
Employed one year after leaving school	1.049***	[1.016, 1.084]	1.051***	[1.017, 1.087]
Employed five years after leaving school	1.027**	[1.002, 1.051]	1.028**	[1.003, 1.052]
Permanent contract three months after leaving school	1.182***	[1.047, 1.336]	1.185***	[1.041, 1.341]
Permanent contract one year after leaving school	1.163***	[1.074, 1.262]	1.169***	[1.077, 1.265]
Permanent contract five years after leaving school	1.118***	[1.063, 1.177]	1.119***	[1.061, 1.176]

Notes. The presented statistics are simulated Average Treatment effects on the Treated and 95% confidence intervals are given between brackets. * (**) (***) indicates significance at the 10% (5%) ((1%)) significance level.

Table 4. ATTs of STEM programmes on schooling and labour market outcomes: total versus direct effect.

	(1)	(2)	(3)
	Correction for unobserved heterogeneity (K = 2)		
	ATTs		
	Total effect	Direct effect	Indirect effect
Secondary education qualification obtained	1.042*** [1.014, 1.072]	1.022* [0.997, 1.047]	0.021*** [0.009, 0.033]
Tertiary education enrolment	0.985 [0.941, 1.033]	0.953** [0.915, 0.995]	0.032*** [0.014, 0.051]
Tertiary education enrolment in STEM programme	6.170*** [4.425, 8.429]	6.215*** [4.500, 8.440]	-0.045 [-0.815, 0.704]
Tertiary education qualification obtained	1.150*** [1.084, 1.220]	1.102*** [1.038, 1.174]	0.048** [0.010, 0.086]
Employed three months after leaving school	1.038 [0.963, 1.113]	1.075* [0.996, 1.155]	-0.036* [-0.076, 0.003]
Employed one year after leaving school	1.051*** [1.017, 1.087]	1.034** [1.002, 1.070]	0.016 [-0.005, 0.038]
Employed five years after leaving school	1.028** [1.003, 1.052]	1.027** [1.005, 1.053]	0.001 [-0.026, 0.020]
Permanent contract three months after leaving school	1.185*** [1.041, 1.341]	1.074 [0.947, 1.208]	0.111*** [0.035, 0.189]
Permanent contract one year after leaving school	1.169*** [1.077, 1.265]	1.057 [0.978, 1.141]	0.112*** [0.065, 0.163]
Permanent contract five years after leaving school	1.119*** [1.061, 1.176]	1.094*** [1.041, 1.155]	0.025 [-0.015, 0.060]

Notes. The presented statistics are simulated Average Treatment effects on the Treated and 95% confidence intervals are given between brackets. * (**) (***) indicates significance at the 10% (5%) (1%) significance level.

Table 5. Estimation results with interaction effects for school track.

A. Outcome: Secondary education qualification obtained		
Track choice end SE: technical track	-1.030**	(0.492)
Track choice end SE: vocational track	-4.049***	(0.426)
Total years in STEM programme end SE	0.126	(0.138)
Total years in STEM programme end SE × Track choice end SE: technical track	0.064	(0.175)
Total years in STEM programme end SE × Track choice end SE: vocational track	-0.039	(0.141)
B. Outcome: Tertiary education enrolment		
Track choice end SE: technical track	-1.333***	(0.258)
Track choice end SE: vocational track	-4.049***	(0.291)
Total years in STEM programme end SE	0.248***	(0.073)
Total years in STEM programme end SE × Track choice end SE: technical track	-0.397***	(0.082)
Total years in STEM programme end SE × Track choice end SE: vocational track	-0.401***	(0.103)
C. Outcome: Tertiary education enrolment in STEM programme		
Track choice end SE: technical track	-0.009	(0.497)
Track choice end SE: vocational track	0.491	(0.795)
Total years in STEM programme end SE	0.536***	(0.047)
Total years in STEM programme end SE × Track choice end SE: technical track	0.302***	(0.075)
Total years in STEM programme end SE × Track choice end SE: vocational track	0.070	(0.240)
D. Outcome: Tertiary education qualification obtained		
Track choice end SE: technical track	-0.722**	(0.289)
Track choice end SE: vocational track	-2.077***	(0.404)
Total years in STEM programme end SE	0.178***	(0.041)
Total years in STEM programme end SE × Track choice end SE: technical track	-0.134**	(0.057)
Total years in STEM programme end SE × Track choice end SE: vocational track	-0.118	(0.192)
E. Outcome: Employed three months after leaving school		
Track choice end SE: technical track	0.122	(0.140)
Track choice end SE: vocational track	0.162	(0.173)
Total years in STEM programme end SE	-0.040	(0.028)
Total years in STEM programme end SE × Track choice end SE: technical track	0.112***	(0.042)
Total years in STEM programme end SE × Track choice end SE: vocational track	0.216***	(0.046)
F. Outcome: Employed one year after leaving school		
Track choice end SE: technical track	-0.032	(0.201)
Track choice end SE: vocational track	0.450*	(0.243)
Total years in STEM programme end SE	0.039	(0.049)
Total years in STEM programme end SE × Track choice end SE: technical track	0.077	(0.070)
Total years in STEM programme end SE × Track choice end SE: vocational track	0.022	(0.074)
G. Outcome: Employed five years after leaving school		
Track choice end SE: technical track	0.554	(0.347)
Track choice end SE: vocational track	0.621	(0.383)
Total years in STEM programme end SE	0.351***	(0.110)
Total years in STEM programme end SE × Track choice end SE: technical track	-0.002	(0.161)
Total years in STEM programme end SE × Track choice end SE: vocational track	-0.358***	(0.131)

Table 5. Estimation results with interaction effects for school track (continued).

H. Outcome: Permanent contract three months after leaving school		
Track choice end SE: technical track	-0.179	0.143
Track choice end SE: vocational track	0.115	0.186
Total years in STEM programme end SE	-0.025	0.030
Total years in STEM programme end SE × Track choice end SE: technical track	0.093**	0.044
Total years in STEM programme end SE × Track choice end SE: vocational track	0.081*	0.045
I. Outcome: Permanent contract one year after leaving school		
Track choice end SE: technical track	-0.342**	0.155
Track choice end SE: vocational track	0.058	0.196
Total years in STEM programme end SE	0.026	0.034
Total years in STEM programme end SE × Track choice end SE: technical track	0.078	0.049
Total years in STEM programme end SE × Track choice end SE: vocational track	-0.060	0.053
J. Outcome: Permanent contract five years after leaving school		
Track choice end SE: technical track	-0.395*	0.216
Track choice end SE: vocational track	-0.465*	0.262
Total years in STEM programme end SE	0.105*	0.058
Total years in STEM programme end SE × Track choice end SE: technical track	0.167**	0.084
Total years in STEM programme end SE × Track choice end SE: vocational track	-0.031	0.077

Note. In these estimations there was correction for unobserved heterogeneity ($K = 2$).

Table 6. Estimation results with interaction effects for gender.

A. Outcome: Secondary education qualification obtained		
Female gender	0.758***	(0.219)
Total years in STEM programme end SE	0.074	(0.053)
Total years in STEM programme end SE × Female gender	0.148	(0.138)
B. Outcome: Tertiary education enrolment		
Female gender	-0.117	(0.172)
Total years in STEM programme end SE	-0.205***	(0.043)
Total years in STEM programme end SE × Female gender	0.384***	(0.075)
C. Outcome: Tertiary education enrolment in STEM programme		
Female gender	-1.691***	(0.253)
Total years in STEM programme end SE	0.629***	(0.045)
Total years in STEM programme end SE × Female gender	0.094	(0.072)
D. Outcome: Tertiary education qualification obtained		
Female gender	0.359**	(0.151)
Total years in STEM programme end SE	0.048	(0.043)
Total years in STEM programme end SE × Female gender	0.151**	(0.061)
E. Outcome: Employed three months after leaving school		
Female gender	-0.185**	(0.094)
Total years in STEM programme end SE	0.060**	(0.027)
Total years in STEM programme end SE × Female gender	-0.019	(0.036)
F. Outcome: Employed one year after leaving school		
Female gender	-0.185**	(0.094)
Total years in STEM programme end SE	0.086**	(0.038)
Total years in STEM programme end SE × Female gender	-0.061	(0.054)
G. Outcome: Employed five years after leaving school		
Female gender	-0.185**	(0.094)
Total years in STEM programme end SE	0.147**	(0.061)
Total years in STEM programme end SE × Female gender	-0.041	(0.107)
H. Outcome: Permanent contract three months after leaving school		
Female gender	-0.308***	(0.081)
Total years in STEM programme end SE	0.036	(0.025)
Total years in STEM programme end SE × Female gender	-0.009	(0.035)
I. Outcome: Permanent contract one year after leaving school		
Female gender	-0.308***	(0.081)
Total years in STEM programme end SE	0.045	(0.028)
Total years in STEM programme end SE × Female gender	-0.047	(0.038)
J. Outcome: Permanent contract five years after leaving school		
Female gender	-0.308***	(0.081)
Total years in STEM programme end SE	0.158***	(0.040)
Total years in STEM programme end SE × Female gender	-0.059	(0.057)

Note. In these estimations there was correction for unobserved heterogeneity (K = 2).

Table 7. Estimation results with interaction effects for migration background.

A. Outcome: Secondary education qualification obtained		
Migration background	-0.462	(0.300)
Total years in STEM programme end SE	0.082	(0.050)
Total years in STEM programme end SE × Migration background	0.271**	(0.137)
B. Outcome: Tertiary education enrolment		
Migration background	-0.480	(0.299)
Total years in STEM programme end SE	-0.093***	(0.035)
Total years in STEM programme end SE × Migration background	0.300**	(0.120)
C. Outcome: Tertiary education enrolment in STEM programme		
Migration background	0.099	(0.628)
Total years in STEM programme end SE	0.671***	(0.036)
Total years in STEM programme end SE × Migration background	-0.181	(0.200)
D. Outcome: Tertiary education qualification obtained		
Migration background	-0.248	(0.388)
Total years in STEM programme end SE	0.117***	(0.033)
Total years in STEM programme end SE × Migration background	0.031	(0.141)
E. Outcome: Employed three months after leaving school		
Migration background	-0.762***	(0.158)
Total years in STEM programme end SE	0.047**	(0.020)
Total years in STEM programme end SE × Migration background	0.036	(0.075)
F. Outcome: Employed one year after leaving school		
Migration background	-0.762***	(0.158)
Total years in STEM programme end SE	0.054*	(0.032)
Total years in STEM programme end SE × Migration background	0.104	(0.109)
G. Outcome: Employed five years after leaving school		
Migration background	-0.762***	(0.158)
Total years in STEM programme end SE	0.136**	(0.055)
Total years in STEM programme end SE × Migration background	-0.033	(0.149)
H. Outcome: Permanent contract three months after leaving school		
Migration background	-0.674***	(0.177)
Total years in STEM programme end SE	0.026	(0.020)
Total years in STEM programme end SE × Migration background	0.037	(0.083)
I. Outcome: Permanent contract one year after leaving school		
Migration background	-0.674***	(0.177)
Total years in STEM programme end SE	0.027	(0.023)
Total years in STEM programme end SE × Migration background	0.033	(0.097)
J. Outcome: Permanent contract five years after leaving school		
Migration background	-0.674***	(0.177)
Total years in STEM programme end SE	0.137***	(0.035)
Total years in STEM programme end SE × Migration background	-0.043	(0.101)

Note. In these estimations there was correction for unobserved heterogeneity (K = 2).

Appendix Table A. Model selection.

(1)	(2)	(3)	(4)	(5)
# heterogeneity types (K)	# parameters	Log-likelihood	Akaike Information Criterion	Bayesian Information Criterion
1	190	-31,353.651	63,087.302	64,310.015
2	199	-31,323.121	63,044.242	64,324.874
3	208	-31,291.029	62,991.207	64,329.756
4	217	-31,287.604	62,941.680	64,338.147
5	226	-31,239.858	62,931.716	64,386.102
6	235	-31,229.518	62,929.035	64,441.338
7	244	-31,224.985	62,937.970	64,508.191
8	253	-31,213.081	62,932.162	64,560.301

Note. These are the results for the model with labour market outcomes 'employed after leaving school'. For the labour market outcomes 'permanent contract after leaving school', also the model with two heterogeneity types is chosen as the preferred model.

Appendix Table B. Full estimation results.

	Coefficient (SE)
A. Delay start 1st year PE	
Female gender	-0.557*** (0.054)
Mother's education after primary education (years)	-0.048*** (0.009)
Father's education after primary education (years)	-0.024*** (0.008)
Number of siblings	0.057*** (0.016)
Day of birth within calendar year	0.001*** (0.000)
Migration background	0.431*** (0.103)
Unemployment rate	0.032*** (0.008)
Cut off 1	-4.377*** (0.232)
Cut off 2	4.392*** (0.240)
B. Additional delay end PE	
Female gender	-0.557*** (0.054)
Mother's education after primary education (years)	-0.048*** (0.009)
Father's education after primary education (years)	-0.024*** (0.008)
Number of siblings	0.057*** (0.016)
Day of birth within calendar year	0.001*** (0.000)
Migration background	0.431*** (0.103)
Unemployment rate	0.032*** (0.008)
Total delay start 1st year PE	-2.539*** (0.229)
Cut off 1	-5.461*** (0.337)
Cut off 2	2.549*** (0.185)
Cut off 3	5.843*** (0.332)
Cut off 4	7.999*** (0.744)
C. Track choice start 1st year SE	
Female gender	-0.271*** (0.062)
Mother's education after primary education (years)	-0.147*** (0.012)
Father's education after primary education (years)	-0.149*** (0.011)
Number of siblings	0.031 (0.019)
Day of birth within calendar year	0.000 (0.000)
Migration background	-0.685*** (0.119)
Unemployment rate	0.024*** (0.008)
Total delay end PE	1.551*** (0.157)
Cut off 1	-3.653*** (0.266)
D. Additional delay end 1st year SE	
Female gender	-0.557*** (0.054)
Mother's education after primary education (years)	-0.048*** (0.009)
Father's education after primary education (years)	-0.024*** (0.008)
Number of siblings	0.057*** (0.016)
Day of birth within calendar year	0.001*** (0.000)
Migration background	0.431*** (0.103)
Unemployment rate	0.032*** (0.008)
Total delay end PE	-0.484** (0.240)
Track choice start 1st year SE: vocational track	-1.296** (0.624)
Cut off 1	3.464*** (0.198)
Cut off 2	8.458*** (1.051)

E. Downgrade start 2nd year SE

Female gender	-0.271***	(0.062)
Mother's education after primary education (years)	-0.147***	(0.012)
Father's education after primary education (years)	-0.149***	(0.011)
Number of siblings	0.031	(0.019)
Day of birth within calendar year	0.000	(0.000)
Migration background	-0.685***	(0.119)
Unemployment rate	0.024***	(0.008)
Total delay end 1st year SE	1.333***	(0.188)
Cut off 1	-4.041***	(0.269)

F. Additional delay end 2nd year SE

Female gender	-0.557***	(0.054)
Mother's education after primary education (years)	-0.048***	(0.009)
Father's education after primary education (years)	-0.024***	(0.008)
Number of siblings	0.057***	(0.016)
Day of birth within calendar year	0.001***	(0.000)
Migration background	0.431***	(0.103)
Unemployment rate	0.032***	(0.008)
Total delay end 1st year SE	-0.102	(0.205)
Track choice start 2nd year SE: vocational track	-0.703**	(0.330)
Cut off 1	3.189***	(0.195)
Cut off 2	6.822***	(0.533)

G. Track choice start 3rd year SE

Female gender	-0.271***	(0.062)
Mother's education after primary education (years)	-0.147***	(0.012)
Father's education after primary education (years)	-0.149***	(0.011)
Number of siblings	0.031	(0.019)
Day of birth within calendar year	0.000	(0.000)
Migration background	-0.685***	(0.119)
Unemployment rate	0.024***	(0.008)
Total delay end 2 nd year SE	1.249***	(0.133)
Cut off 1	-1.898***	(0.272)
Cut off 2	1.396***	(0.215)

H. STEM programme start 3rd year SE

Female gender	-1.282***	(0.044)
Mother's education after primary education (years)	0.000	(0.008)
Father's education after primary education (years)	0.025***	(0.007)
Number of siblings	0.000	(0.017)
Day of birth within calendar year	0.000	(0.000)
Migration background	0.015	(0.107)
Unemployment rate	-0.001	(0.007)
Total delay end 2nd year SE	-0.371***	(0.096)
Track choice start 3rd year SE: technical track	-0.811***	(0.113)
Track choice start 3rd year SE: vocational track	-0.833***	(0.128)
Cut off 1	1.156***	(0.184)

I. Additional delay end 3rd year SE

Female gender	-0.557***	(0.054)
Mother's education after primary education (years)	-0.048***	(0.009)
Father's education after primary education (years)	-0.024***	(0.008)

Number of siblings	0.057***	(0.016)
Day of birth within calendar year	0.001***	(0.000)
Migration background	0.431***	(0.103)
Unemployment rate	0.032***	(0.008)
Total delay end 2nd year SE	0.074	(0.151)
Track choice start 3rd year SE: technical track	0.605***	(0.170)
Track choice start 3rd year SE: vocational track	-0.238	(0.224)
Total years in STEM programme start 3rd year SE	-0.275*	(0.145)
Cut off 1	2.974***	(0.231)
Cut off 2	6.971***	(0.556)

J. Downgrade start 4th year SE

Female gender	-0.271***	(0.062)
Mother's education after primary education (years)	-0.147***	(0.012)
Father's education after primary education (years)	-0.149***	(0.011)
Number of siblings	0.031	(0.019)
Day of birth within calendar year	0.000	(0.000)
Migration background	-0.685***	(0.119)
Unemployment rate	0.024***	(0.008)
Total delay end 3rd year SE	1.495***	(0.153)
Track choice start 3rd year SE: technical track	-1.926***	(0.244)
Total years in STEM programme start 3rd year SE	-0.735***	(0.180)
Cut off 1	-0.254	(0.314)
Cut off 2	3.883***	(0.490)

K. STEM programme start 4th year SE

Female gender	-1.282***	(0.044)
Mother's education after primary education (years)	0.000	(0.008)
Father's education after primary education (years)	0.025***	(0.007)
Number of siblings	0.000	(0.017)
Day of birth within calendar year	0.000	(0.000)
Migration background	0.015	(0.107)
Unemployment rate	-0.001	(0.007)
Total delay end 3rd year SE	-0.531***	(0.141)
Track choice start 4th year SE: technical track	-0.543***	(0.197)
Track choice start 4th year SE: vocational track	0.124	(0.292)
Total years in STEM programme start 3rd year SE	5.753***	(0.162)
Cut off 1	-2.595***	(0.236)

L. Additional delay end 4th year SE

Female gender	-0.557***	(0.054)
Mother's education after primary education (years)	-0.048***	(0.009)
Father's education after primary education (years)	-0.024***	(0.008)
Number of siblings	0.057***	(0.016)
Day of birth within calendar year	0.001***	(0.000)
Migration background	0.431***	(0.103)
Unemployment rate	0.032***	(0.008)
Total delay end 3rd year SE	-0.068	(0.149)
Track choice start 4th year SE: technical track	0.240	(0.158)
Track choice start 4th year SE: vocational track	-0.906***	(0.229)
Total years in STEM programme start 4th year SE	-0.239***	(0.068)
Cut off 1	2.429***	(0.225)

Cut off 2	6.224***	(0.443)
M. Downgrade start 5th year SE		
Female gender	-0.271***	(0.062)
Mother's education after primary education (years)	-0.147***	(0.012)
Father's education after primary education (years)	-0.149***	(0.011)
Number of siblings	0.031	(0.019)
Day of birth within calendar year	0.000	(0.000)
Migration background	-0.685***	(0.119)
Unemployment rate	0.024***	(0.008)
Total delay end 4th year SE	1.312***	(0.134)
Track choice start 4th year SE: technical track	-2.097***	(0.260)
Total years in STEM programme start 4th year SE	-0.432***	(0.087)
Cut off 1	-0.763**	(0.345)
Cut off 2	3.604***	(0.522)
N. STEM programme start 5th year SE		
Female gender	-1.282***	(0.044)
Mother's education after primary education (years)	0.000	(0.008)
Father's education after primary education (years)	0.025***	(0.007)
Number of siblings	0.000	(0.017)
Day of birth within calendar year	0.000	(0.000)
Migration background	0.015	(0.107)
Unemployment rate	-0.001	(0.007)
Total delay end 4th year SE	-0.377***	(0.117)
Track choice start 5th year SE: technical track	0.630***	(0.210)
Track choice start 5th year SE: vocational track	0.185	(0.273)
Total years in STEM programme start 4th year SE	2.162***	(0.073)
Cut off 1	-1.972***	(0.260)
O. Additional delay end 5th year SE		
Female gender	-0.557***	(0.054)
Mother's education after primary education (years)	-0.048***	(0.009)
Father's education after primary education (years)	-0.024***	(0.008)
Number of siblings	0.057***	(0.016)
Day of birth within calendar year	0.001***	(0.000)
Migration background	0.431***	(0.103)
Unemployment rate	0.032***	(0.008)
Total delay end 4th year SE	0.220**	(0.102)
Track choice start 5th year SE: technical track	0.293**	(0.147)
Track choice start 5th year SE: vocational track	-0.811***	(0.185)
Total years in STEM programme start 5th year SE	-0.073*	(0.041)
Cut off 1	2.219***	(0.227)
Cut off 2	5.195***	(0.309)
Cut off 3	8.439***	(1.080)
P. Downgrade end SE		
Female gender	-0.271***	(0.062)
Mother's education after primary education (years)	-0.147***	(0.012)
Father's education after primary education (years)	-0.149***	(0.011)
Number of siblings	0.031	(0.019)
Day of birth within calendar year	0.000	(0.000)
Migration background	-0.685***	(0.119)

Unemployment rate	0.024***	(0.008)
Total delay end 5th year SE	1.543***	(0.151)
Track choice start 5th year SE: technical track	-1.264***	(0.324)
Total years in STEM programme start 5th year SE	-0.381***	(0.090)
Cut off 1	0.879**	(0.402)
Cut off 2	4.081***	(0.552)

Q. STEM programme end SE

Female gender	-1.282***	(0.044)
Mother's education after primary education (years)	0.000	(0.008)
Father's education after primary education (years)	0.025***	(0.007)
Number of siblings	0.000	(0.017)
Day of birth within calendar year	0.000	(0.000)
Migration background	0.015	(0.107)
Unemployment rate	-0.001	(0.007)
Total delay end 5th year SE	-0.500***	(0.094)
Track choice end SE: technical track	1.372***	(0.239)
Track choice end SE: vocational track	3.044***	(0.261)
Total years in STEM programme start 5th year SE	2.531***	(0.081)
Cut off 1	4.346***	(0.297)
Cut off 2	10.670***	(0.411)

R. Additional delay end SE

Female gender	-0.557***	(0.054)
Mother's education after primary education (years)	-0.048***	(0.009)
Father's education after primary education (years)	-0.024***	(0.008)
Number of siblings	0.057***	(0.016)
Day of birth within calendar year	0.001***	(0.000)
Migration background	0.431***	(0.103)
Unemployment rate	0.032***	(0.008)
Total delay end 5th year SE	0.255***	(0.095)
Track choice end SE: technical track	0.503***	(0.186)
Track choice end SE: vocational track	0.664***	(0.190)
Total years in STEM programme end SE	-0.104***	(0.036)
Cut off 1	3.024***	(0.245)
Cut off 2	5.398***	(0.304)
Cut off 3	6.504***	(0.429)

S. Secondary education qualification

Female gender	0.891***	(0.197)
Mother's education after primary education (years)	0.024	(0.025)
Father's education after primary education (years)	0.070***	(0.024)
Number of siblings	-0.085*	(0.045)
Day of birth within calendar year	0.002**	(0.000)
Migration background	-0.013	(0.245)
Unemployment rate	0.010	(0.023)
Total delay end SE	-0.290***	(0.076)
Track choice end SE: technical track	-0.949***	(0.332)
Track choice end SE: vocational track	-4.159***	(0.294)
Total years in STEM programme end SE	0.101**	(0.049)
Intercept	3.874***	(0.487)

T. Tertiary education enrolment

Female gender	0.489***	(0.133)
Mother's education after primary education (years)	0.057***	(0.020)
Father's education after primary education (years)	0.095***	(0.019)
Number of siblings	-0.029	(0.040)
Day of birth within calendar year	0.001***	(0.000)
Migration background	0.079	(0.237)
Unemployment rate	-0.004	(0.019)
Total delay end SE	-0.382***	(0.072)
Track choice end SE: technical track	-2.170***	(0.210)
Track choice end SE: vocational track	-4.836***	(0.245)
Total years in STEM programme end SE	-0.077**	(0.033)
Intercept	2.362***	(0.421)

U. Tertiary education STEM enrolment

Female gender	-1.391***	(0.106)
Mother's education after primary education (years)	-0.033	(0.024)
Father's education after primary education (years)	0.010	(0.022)
Number of siblings	0.033	(0.049)
Day of birth within calendar year	0.000	(0.000)
Migration background	-0.436	(0.333)
Unemployment rate	0.008	(0.019)
Total delay end SE	-0.236**	(0.105)
Track choice end SE: technical track	0.827*	(0.425)
Track choice end SE: vocational track	0.732	(0.657)
Total years in STEM programme end SE	0.665***	(0.035)
Intercept	-2.433***	(0.783)

V. Tertiary education qualification

Female gender	0.622***	(0.114)
Mother's education after primary education (years)	0.044*	(0.022)
Father's education after primary education (years)	0.067***	(0.019)
Number of siblings	0.083**	(0.037)
Day of birth within calendar year	0.000	(0.000)
Migration background	-0.188	(0.259)
Unemployment rate	-0.112***	(0.030)
Total delay end SE	-0.844***	(0.090)
Track choice end SE: technical track	-0.993***	(0.264)
Track choice end SE: vocational track	-2.290***	(0.366)
Total years in STEM programme end SE	0.119***	(0.032)
Tertiary education STEM enrolment	0.204	(0.141)
Intercept	1.116**	(0.548)

W. Employed three months after leaving school

Female gender	-0.244***	(0.062)
Mother's education after primary education (years)	-0.005	(0.011)
Father's education after primary education (years)	-0.028***	(0.010)
Number of siblings	-0.067***	(0.019)
Day of birth within calendar year	-0.001**	(0.000)
Migration background	-0.677***	(0.119)
Unemployment rate	-0.093***	(0.013)
Total delay end SE	-0.030	(0.049)

Track choice end SE: technical track	0.381***	(0.109)
Track choice end SE: vocational track	0.560***	(0.150)
Total years in STEM programme end SE	0.049**	(0.019)
Secondary education qualification	0.175	(0.139)
Tertiary education enrolment	-0.190	(0.123)
Tertiary education STEM enrolment	-0.339***	(0.098)
Tertiary education qualification	0.535***	(0.097)
Intercept	1.355***	(0.278)

X. Employed one year after leaving school

Female gender	-0.244***	(0.062)
Mother's education after primary education (years)	-0.005	(0.011)
Father's education after primary education (years)	-0.028***	(0.010)
Number of siblings	-0.067***	(0.019)
Day of birth within calendar year	-0.001**	(0.000)
Migration background	-0.677***	(0.119)
Unemployment rate	-0.093***	(0.013)
Total delay end SE	0.071	(0.069)
Track choice end SE: technical track	0.109	(0.154)
Track choice end SE: vocational track	0.503**	(0.212)
Total years in STEM programme end SE	0.063**	(0.031)
Secondary education qualification	0.464**	(0.198)
Tertiary education enrolment	-0.061	(0.169)
Tertiary education STEM enrolment	0.068	(0.174)
Tertiary education qualification	1.379***	(0.146)
Employed three months after leaving school	2.275***	(0.121)
Intercept	0.990***	(0.335)

Y. Employed five years after leaving school

Female gender	-0.244***	(0.062)
Mother's education after primary education (years)	-0.005	(0.011)
Father's education after primary education (years)	-0.028***	(0.010)
Number of siblings	-0.067***	(0.019)
Day of birth within calendar year	-0.001**	(0.000)
Migration background	-0.677***	(0.119)
Unemployment rate	-0.093***	(0.013)
Total delay end SE	0.117	(0.136)
Track choice end SE: technical track	0.512*	(0.296)
Track choice end SE: vocational track	0.096	(0.336)
Total years in STEM programme end SE	0.132**	(0.053)
Secondary education qualification	0.474*	(0.257)
Tertiary education enrolment	0.444	(0.307)
Tertiary education STEM enrolment	-0.327	(0.396)
Tertiary education qualification	1.052***	(0.338)
Employed three months after leaving school	0.139	(0.212)
Employed one year after leaving school	1.347***	(0.215)
Intercept	1.695***	(0.430)

Z. Unobserved heterogeneity distribution

δ_2^1 : (additional) delay	0.095	(0.148)
δ_2^2 : track choice/downgrading	2.306***	(0.242)
δ_2^3 : STEM programme	0.089	(0.155)

δ_2^4 : Secondary education qualification	-0.555***	(0.188)
δ_2^5 : Tertiary education enrolment	-0.131	(0.285)
δ_2^6 : Tertiary education STEM enrolment	-0.189	(0.775)
δ_2^7 : Tertiary education qualification	0.290	(0.477)
δ_2^8 : Employed after leaving school	-0.177	(0.130)
q ₂	0.316	(0.220)
N	4,607	

Notes. The presented statistics are estimated coefficients and standard errors between parentheses. * (**) (***) indicates significance at the 10% (5%) ((1%)) significance level.

Appendix Table C. Full estimation results for the labour market outcomes ‘Permanent contract after leaving school’.

	Coefficient (SE)	
A.–V. See Appendix Table B.		
W. Permanent contract three months after leaving school		
Female gender	-0.366***	(0.054)
Mother’s education after primary education (years)	-0.012	(0.009)
Father’s education after primary education (years)	-0.010	(0.009)
Number of siblings	-0.030	(0.018)
Day of birth within calendar year	0.000*	(0.000)
Migration background	-0.643***	(0.127)
Unemployment rate	-0.062***	(0.011)
Total delay end SE	-0.036	(0.053)
Track choice end SE: technical track	0.025	(0.107)
Track choice end SE: vocational track	0.278*	(0.157)
Total years in STEM programme end SE	0.028	(0.020)
Secondary education qualification	0.305**	(0.142)
Tertiary education enrolment	-0.501***	(0.137)
Tertiary education STEM enrolment	0.249**	(0.105)
Tertiary education qualification	0.411***	(0.110)
Intercept	0.059	(0.273)
X. Permanent contract one year after leaving school		
Female gender	-0.366***	(0.054)
Mother’s education after primary education (years)	-0.012	(0.009)
Father’s education after primary education (years)	-0.010	(0.009)
Number of siblings	-0.030	(0.018)
Day of birth within calendar year	0.000*	(0.000)
Migration background	-0.643***	(0.127)
Unemployment rate	-0.062***	(0.011)
Total delay end SE	-0.034	(0.061)
Track choice end SE: technical track	-0.221*	(0.117)
Track choice end SE: vocational track	-0.100	(0.170)
Total years in STEM programme end SE	0.027	(0.022)
Secondary education qualification	0.156	(0.164)
Tertiary education enrolment	-0.176	(0.144)
Tertiary education STEM enrolment	0.439***	(0.121)
Tertiary education qualification	0.255**	(0.115)
Permanent contract three months after leaving school	3.163***	(0.116)
Intercept	0.273	(0.279)
Y. Permanent contract five years after leaving school		
Female gender	-0.366***	(0.054)
Mother’s education after primary education (years)	-0.012	(0.009)
Father’s education after primary education (years)	-0.010	(0.009)
Number of siblings	-0.030	(0.018)
Day of birth within calendar year	0.000*	(0.000)
Migration background	-0.643***	(0.127)
Unemployment rate	-0.062***	(0.011)
Total delay end SE	0.089	(0.093)

Track choice end SE: technical track	-0.156	(0.166)
Track choice end SE: vocational track	-0.551**	(0.226)
Total years in STEM programme end SE	0.133***	(0.033)
Secondary education qualification	0.408**	(0.194)
Tertiary education enrolment	-0.001	(0.202)
Tertiary education STEM enrolment	0.042	(0.219)
Tertiary education qualification	-0.152	(0.179)
Permanent contract three months after leaving school	0.204	(0.183)
Permanent contract one year after leaving school	1.557***	(0.161)
Intercept	1.513***	(0.324)

Z. See Appendix Table B.

Notes. The presented statistics are estimated coefficients and standard errors between parentheses. * (**) (***) indicates significance at the 10% (5%) ((1%)) significance level.

Appendix Table D. Goodness of fit.

	(1)	(2)	
	Actual probability	Simulated probability [95% CI]	
Primary education			
Delay start 1st year PE	-0.001	-0.001	[-0.009, 0.006]
Additional delay end PE	0.079	0.079	[0.067, 0.093]
Secondary education			
Track choice start 1st year SE	0.064	0.061	[0.051, 0.072]
Additional delay end 1st year SE	0.030	0.030	[0.023, 0.038]
Downgrade start 2nd year SE	0.039	0.039	[0.030, 0.048]
Additional delay end 2nd year SE	0.040	0.041	[0.031, 0.049]
Track choice start 3rd year SE	0.430	0.432	[0.406, 0.458]
STEM programme start 3rd year SE	0.557	0.556	[0.533, 0.577]
Additional delay end 3rd year SE	0.055	0.056	[0.046, 0.067]
Downgrade start 4th year SE	0.070	0.070	[0.058, 0.083]
STEM programme start 4th year SE	0.529	0.525	[0.500, 0.548]
Additional delay end 4th year SE	0.064	0.065	[0.054, 0.076]
Downgrade start 5th year SE	0.084	0.086	[0.073, 0.099]
STEM programme start 5th year SE	0.518	0.516	[0.493, 0.539]
Additional delay end 5th year SE	0.096	0.097	[0.084, 0.111]
Downgrade end SE	0.033	0.034	[0.025, 0.044]
STEM programme end SE	0.569	0.566	[0.539, 0.593]
Additional delay end SE	0.066	0.067	[0.056, 0.080]
Secondary education qualification	0.906	0.906	[0.892, 0.918]
Tertiary education			
Tertiary education enrolment	0.766	0.772	[0.753, 0.791]
Tertiary education STEM enrolment	0.256	0.264	[0.239, 0.290]
Tertiary education qualification	0.763	0.762	[0.739, 0.784]
Early labour market			
Employed three months after leaving school	0.624	0.628	[0.607, 0.649]
Employed one year after leaving school	0.862	0.881**	[0.866, 0.896]
Employed five years after leaving school	0.935	0.949**	[0.936, 0.961]
Permanent contract three months after leaving school	0.314	0.331	[0.310, 0.352]
Permanent contract one year after leaving school	0.521	0.544*	[0.520, 0.566]
Permanent contract five years after leaving school	0.799	0.803	[0.780, 0.824]

Note. * (**) (***) indicates a significant difference between the actual and simulated probabilities at the 10% (5%) ((1%)) significance level.

Appendix Table E. ATTs versus ATNTs of STEM programmes on schooling and labour market outcomes.

	(1)		(2)	
	Correction for unobserved heterogeneity (K = 2)			
	Total effect		Total effect	
	ATTs		ATNTs	
Secondary education qualification obtained	1.042***	[1.014, 1.072]	1.045***	[1.012, 1.079]
Tertiary education enrolment	0.985	[0.941, 1.033]	0.979	[0.926, 1.036]
Tertiary education enrolment in STEM programme	6.170***	[4.425, 8.429]	7.393***	[5.132, 10.686]
Tertiary education qualification obtained	1.150***	[1.084, 1.220]	1.149***	[1.075, 1.226]
Employed three months after leaving school	1.038	[0.963, 1.113]	1.046	[0.973, 1.130]
Employed one year after leaving school	1.051***	[1.017, 1.087]	1.053***	[1.013, 1.089]
Employed five years after leaving school	1.028**	[1.003, 1.052]	1.032**	[1.006, 1.058]
Permanent contract three months after leaving school	1.185***	[1.041, 1.341]	1.182**	[1.027, 1.350]
Permanent contract one year after leaving school	1.169***	[1.077, 1.265]	1.167***	[1.056, 1.275]
Permanent contract five years after leaving school	1.119***	[1.061, 1.176]	1.139***	[1.068, 1.204]

Notes. The presented statistics are simulated Average Treatment effects on the (Non-)Treated and 95% confidence intervals are given between brackets. * (**) (***) indicates significance at the 10% (5%) ((1%)) significance level.