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The Effect of a Five-Day Intervention on STEM Enrolment in Vocational Education and Training:

Evidence from the Netherlands

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Abstract

While many job opportunities are available for Science, Technology, Engineering and Mathematics (STEM) graduates, STEM programmes offered in vocational education suffer from low student enrolment. This study examines the effectiveness of a five-day programme conducted in the Amsterdam Metropolitan Area in 2014-15. The intervention aimed at encouraging students from preparatory vocational education to choose for STEM education in upper-secondary vocational education and training. The difference-in-differences analysis indicates that the intervention did not affect native Dutch male students' likelihood to enrol into STEM. For male students with a migrant background, the intervention increased the probability of STEM-enrolment with 0.6%-points.

1. Introduction

The demand for graduates in Science, Technology, Engineering and Mathematics (STEM) has increased in most European Union countries, including the Netherlands, and is expected to grow further in the coming years (BusinessEurope 2011; Cedefop 2014a; Cedefop 2014b; European Commission 2014; ROA 2017). This does not only hold for STEM graduates from higher education, but also for graduates from upper-secondary vocational education and training (VET). Despite the fact that STEM is often associated with the image of highly educated scientists in white lab coats, VET graduates traditionally form an important supply source for STEM-related skills. In fact, 48% of STEM-related occupations require medium level qualifications that are typically acquired through upper-secondary VET (Cedefop 2014b). STEM education in VET prepares students for a wide range of occupations including construction workers, electricians, mechanical technicians, maintenance and repair workers, and sheet metal workers. While the supply of university graduates with STEM-credentials on the EU-28 labour market slightly increased from 22% in 2007 to 23% in 2012, the share of VET graduates with a STEM degree decreased from 32% in 2006 to 30% in 2011 (Cedefop 2014a; Cedefop 2014b). Likewise, in the Netherlands, the share of VET graduates with a STEM degree declined from 30% in 2006 to 27% in 2015 (www.techniekpactmonitor.nl).

This latter result can go hand in hand with non-negligible consequences in light of the increasing demand for workers with a STEM degree from VET and the destruction of jobs that are typically held by VET graduates (Autor et al. 2003; Autor and Dorn 2013; Goos et al. 2014; Michaels et al. 2014; Van den Berge and Ter Weel 2015). Poor demand on the labour market for a specific field-of-study can force graduates to accept a job that is unrelated to the attended field- and/or level of education (Borghans and De Grip 2000; Wolbers 2003). Such education-job mismatches can result in an underutilization of skills, wage penalties, job dissatisfaction, and regret of the chosen field-of-study (Groot and Maassen van den Brink 2000; Allen and Van der Velden 2001; Borghans and Golsteyn 2005; Robst 2007; Green and Zhu 2010; Béduwé and Giret 2011; Shevchuk et al. 2015).

This study investigates the effectiveness of a newly designed five-day programme for 15-year-old students in preparatory vocational education (pre-VET) in the Amsterdam Metropolitan Area, who are about to choose their field-of-study in VET. The main target of the programme is to encourage students from pre-VET to choose for a STEM programme. There is a high demand for STEM graduates on the regional labour market of the Amsterdam Metropolitan Area (www.s-bb.nl). As such, the five-day intervention targets to improve the connection between education and the labour market in the long run.[1]

Students might make sub-optimal study choices due to uncertainty regarding their preferences, ability, as well as labour market outcomes (Betts 1996; Altonji et al. 2012; Wiswall and Zafar 2015a). The five-day programme provides students the opportunity to acquire hands-on-experience with a variety of STEM occupations. Students carry out occupation-related assignments that allow them to learn about the match between the content of occupations and their abilities and preferences (Altonji et al. 2012; Wiswall and Zafar 2015a). During the five-day intervention, students are also informed about the labour market demand for graduates from different STEM programmes. This might affect students' choice behaviour as they tend to update their beliefs about their labour market outcomes when confronted with information on it (Woods and O'Leary 2006; Jensen 2010; Zafar 2011; Oreopoulos and Dunn 2013; Hastings et al. 2015; Wiswall and Zafar 2015a; McGuigan et al. 2016).

There are at least four contributions of this study to the literature. Numerous studies evaluate the effectiveness of interventions that aim to increase the enrolment of middle- and high school students in STEM education and careers (e.g. Dawes et al. 2000; Gibson and Chase 2002; Welch 2010; Wyss et al. 2012; Bamberger 2014; Constan and Spicer 2015). Interventions encompass company visits, summer camps, after school programmes or altered curricula. The majority of these studies explore the effect of interventions on short-term outcomes including students' interest in STEM careers, attitude towards STEM careers, technical self-efficacy, and achievement in STEM courses. In contrast to earlier research, this study examines the effect of a five-day study choice programme on actual enrolments rates into STEM education.

Second, most of the evaluated STEM interventions were targeted at students in the United States (Dawes et al. 2000; Gibson and Chase 2002; Jayaratne et al. 2003; Nugent et al. 2009; Welch 2010; Greenes et al. 2011; Wyss et al. 2012; Hiller and Kitsantas 2014; Constan and Spicer 2015). The American education system is characterized by a weak tracking system and, consequently, treatment groups can be rather heterogeneous (Bol and Van de Werfhorst 2016). This matters as students with higher cognitive abilities tend to form more realistic expectations of their labour market outcomes which determines, in turn, the quality of schooling choices (Borghans and Golsteyn 2005). For the evaluation of the intervention at hand, we benefit from a homogeneous group of treated students. The Dutch education system is characterized by the selection of students into differing-ability tracks at an early age (i.e. at age 12). Students in pre-VET make their schooling choices earlier than students in the higher tracks (16 vs. 17 or 18). Younger students, as well as students who are less academically oriented, might need different interventions in order to make an adequate study choice than older academically oriented students.

1 A second aim of the intervention was to improve the match between a specific study programme within the STEM sector in VET and students who were already interested in enrolling into STEM education. Thereby, the intervention could potentially reduce the likelihood that treated students drop out in the first year in VET. Due to data restrictions, we only examine the effectiveness of the intervention in terms of enrolment into STEM.

The third contribution of our study concerns our evaluation methodology. Previous studies often did not properly account for differences in the treatment and control group in the absence of random assignment to the treatment (e.g. Welch 2010; Greenes et al. 2011; Bamberger 2014; Hiller and Kitsantas 2014; Kim and Chae 2016). For example, Greenes et al. (2011) applied a matching technique, but on a sample consisting of students who decided not to participate in the intervention. We analyse the causal impact of this five-day intervention on enrolment rates into STEM using a difference-in-differences framework. This approach is supported by having rich and complete panel data on the educational career of each student in the Netherlands.

Finally, our analyses will be performed separately for native Dutch students and students with a migrant background. The share of students who are enrolled into STEM education in VET in the Netherlands is substantially lower for students with a migrant background than for native students (www.techniekpactmonitor.nl). An important explanation for this underrepresentation is that STEM occupations suffer from a negative image among students with a migrant background (Kuijpers and Meijers 2009; De Koning et al. 2010). Moreover, students with a migrant background tend to be less confident about their ability to successfully complete a STEM programme and are less well-informed about the labour market perspectives of different educational pathways (De Koning et al. 2010; MacPhee et al. 2013). As such, students' beliefs regarding their preference, ability, and labour market outcomes is likely to be more biased for migrant students. Consequently, the potential of the intervention for updating students' beliefs about STEM might have been larger for migrant students than for native students.

Our findings indicate that higher participation rates in the intervention at the school level significantly increased the likelihood that male students with a migrant background choose to enrol into STEM education in VET.[2] A 1%-point increase in the share of male students who participate in the intervention, significantly increased the likelihood of enrolling into STEM with 0.6%-points. In contrast, the intervention had no effect on native male students.
This paper proceeds as follows. Section 2 provides a description of the intervention. Section 3 presents the identification strategy and Section 4 describes the data. The results are presented in Section 5 and Section 6 discusses the robustness of these results. The conclusion and discussion are provided in Section 7.

2 The effectiveness of the intervention is only examined for male students as the share of female participants was smaller than 1%.

2. Course of the intervention

The five-day study choice programme carries the official label ‘professional orientation and on-the-job assessment’ (Dutch: *Beroepsoriëntatie & Praktijk-assessment*). The programme was part of a bigger project called ‘Make Talent Work’ (Dutch: *Werk Maken van Talent*) that consisted of 10 different intervention programmes in the Amsterdam Metropolitan Area. The ‘professional orientation and on-the-job assessment’ was one out of 10 interventions. The project has been funded for two years between 2015-2017 by different parties including the Ministry of Social Affairs and Employment, regional business and educational institutions. The project’s long-run aims were to improve the connection between skill supply and demand on the labour market and to prevent skill mismatch.

The intervention was designed for students who are about to complete pre-VET (i.e. at age 15-16 without grade interruptions or grade retention and depending on date of birth). The intervention was introduced in the academic year 2014-15 and also offered to consecutive cohorts. Since we lack the data for the cohorts 2015-16 and beyond, we restrict our analyses to those students who participated in the intervention in the academic year 2014-15.

Upon successful completion of pre-VET, students can enrol into STEM or another sector (health & welfare, economics or agriculture) in VET. In 2014-15, the intervention was promoted among pre-VET students in the Amsterdam Metropolitan Area. The intervention is carried out in six training companies. In cooperation with the VET-schools located in the Amsterdam Metropolitan Area, the training companies provide in-school practical training within the STEM programmes. The programme lasts five days and consists of a four-day module on professional orientation and a one-day generic module.[3] The module on professional orientation introduces participants to STEM occupations with good labour market perspectives in the Amsterdam Metropolitan Area. These include occupations in the sectors building & construction, installation and electrical engineering, metal engineering, woodwork & furniture, and motor vehicle engineering. During the intervention, students get acquainted with up to three of these STEM sectors. In the professional orientation module, students carry out different assignments that relate to the sectors of interest. Each assignment is related to multiple disciplines, e.g. carpentry combined with painting and finishing techniques or metal technology combined with installation technology. All assignments enable students to apply vocational knowledge to practice at different difficulty levels. For the generic module, participants are assessed on their cognitive, vocational, and interpersonal skills. Based on these assessment, participants are provided with education advice.

3 Based on the preferences of the students and the school mentor, these five days could take place anytime in the school year.

The intervention can affect students' choice to enrol into STEM education through various channels. First, the intervention serves as an opportunity for students to get hands-on-experience with a variety of STEM occupations which allows them to obtain a realistic view of what occupations entail. This might remove prejudices that students hold against certain occupations, but also provide insight into how occupations match students' tastes and preferences (Altonji et al. 2012; Wiswall and Zafar 2015a). Second, the intervention informs students about which STEM occupations match their ability and skills (Jackson 1982; Altonji et al. 2012; Wiswall and Zafar 2015a). Finally, students are informed about the linkage between the skills learned in different STEM programmes and the labour market demand for such skills. Providing students with labour market information can alter students' expectations and subsequently affect their educational choices (Woods and O'Leary 2006; Jensen 2010; Oreopoulos and Dunn 2013; Hastings et al. 2015; Wiswall and Zafar 2015a; McGuigan et al. 2016).

3. Identification strategy

We estimate the effect of the five-day intervention on the likelihood of enrolment into a STEM programme in VET. Given that students were not randomly assigned to the intervention, we exploit the sudden and prompt way the intervention was implemented within a difference-in-differences (*DiD*) framework. An interview with one of the organizing training companies pointed out that the intervention was promoted at several pre-VET schools in the Amsterdam Metropolitan Area. The promotion of the intervention was targeted at schools that have a substantial share of students taking STEM subjects as they are most likely to enrol in STEM education in VET.[4,5] The intervention was also promoted at open days of VET institutes and training companies. Due to the selective promotion, there were only few students who participated in the intervention and who lived outside the Amsterdam Metropolitan Area.[6] As such, we can construct a control group from students who attended schools located outside the Amsterdam Metropolitan Area.

In the *DiD* model, we compare the outcomes of students in treated schools who graduated from pre-VET ($D = 1$) in the post-treatment period ($T = 1$) with the outcomes of untreated students ($D = 1$) in the pre-treatment period ($T = 0$). Furthermore, we compare students in the treated schools ($D = 1$) with students in untreated schools ($D = 0$) in the pre- and post-treatment period, respectively. The post-treatment period refers to the schoolyear 2014-15, while the pre-treatment period concerns the schoolyears 2011-12, 2012-13, and 2013-14. The *DiD* estimator is calculated as the difference in the average probability to enrol into STEM education in the treatment group before and after the intervention, minus the difference in the average likelihood to enrol into STEM in the control group before and after the treatment. The DiD baseline equation of interest is as follows:

$$STEM\ enrollment_i = ß_0 + ß_1 D_j + ß_2 T_p + ß_3 (D_j * T_p) + ß_4 X_{ij} + \varepsilon_i \quad (1)$$

Here, the outcome variable $STEM\ enrollment_i$ equals 1 if student $i \in \{1, 2, ..., N\}$ enrols in STEM in VET upon completion of pre-VET, and 0 otherwise. The treatment status of student i is denoted by D_j. We will use two indicators for D_j. First, we use a binary treatment indicator where D_j equals 1 if student i attended school j where at least one student participated in the intervention, and D_j equals 0 if student i attended a school where no students were exposed

4 These schools were targeted given that another aim of the intervention was to improve the match between STEM programmes and students who were already interested in STEM education.

5 Information about the relation between STEM enrolment and the pre-VET background can be retrieved from www.doorstroomatlas-vmbo.nl.

6 This substantially reduces the likelihood that students who attended schools outside the Amsterdam Metropolitan Area were actually aware of the study choice programme. This was confirmed in an interview with one of the training companies.

to the intervention. Second, we use a continuous treatment indicator where D_j represents the % of male students in the final year of pre-VET who participated in the intervention at school *j* of student *i*. Given that not every student in a treated school actually participates in the intervention, we estimate an intention-to-treat (ITT) effect. The time indicator is denoted by T_p with $T = 0$ indicating the pre-treatment period (2011-12, 2012-13, and 2013-14) and $T = 1$ the post-treatment period (2014-15). Vector X_{ij} constitutes a set of observable characteristics introduced in Section 4. The *DiD* estimator contains a treatment fixed effect $D_j \in \{0,1\}$ to account for all time invariant characteristics of the treatment and control schools. The *DiD* estimator also contains a time fixed effect $T_p \in \{0,1\}$ to control for factors that can cause the outcome to differ across cohorts (i.e. national policies that aim to increase enrolment into STEM). The main parameter of interest is β_3.

The *DiD* estimator relies on several assumptions. The first assumption concerns the common time trend (Bertrand et al. 2004). This assumption implies that, in absence of the intervention, the average enrolment rate into STEM education moves parallel over time in the control and treatment group. In other words, the estimated effect is a direct result of the intervention and not of any other event. This should hold for native Dutch students as well as for students with a migrant background. To formally test the parallel time trend assumption, we estimate an alternative difference-in-differences model including leads and lags. The analysis of leads enables us to test whether the trends in the pre-treatment are similar, while lags indicate whether the treatment effect changes after the introduction of the treatment (Autor, 2003). The following equation describes the model with leads and lags:

$$STEM\ enrollment_i = \alpha_0 + \alpha_1 D_j + \sum_{t=2011}^{2014} (D_j * Year_t)\, \alpha_{2,t} + \alpha_3 X_{ij} + \gamma_t + \varepsilon_i \quad (2)$$

Here, the coefficients $\alpha_{2,t}$ represent the interactions between the indicator variables for each schoolyear and an indicator for whether a pre-VET school is treated or not. Whether the parallel time trend assumption holds will be discussed in the results section (Section 5).

The second assumption for the *DiD* estimation to hold is the Stable Unit Treatment Value (SUTVA) assumption. SUTVA deals with potential spill-over effects of the intervention from treated to untreated students. Spill-over effects from the treatment to the control group are minimized because, at the time of the intervention, treated and untreated students attended schools in different regions. As argued above, the control students attended schools outside the Amsterdam Metropolitan Area and they were unlikely to be aware of the intervention. Therefore, we argue that the SUTVA-assumption is not violated.

It is important to point out that similar interventions might have taken place outside the Amsterdam Metropolitan Area that we are unaware of. However, the five-day programme was part of a large-scale intervention that was unique to the Amsterdam Metropolitan Area. Therefore, our study provides lower bound estimates of the effect of the intervention on STEM enrolment.

4. Data and descriptive statistics

This study uses the BRON data (Dutch: BasisRegister Onderwijsnummer). The BRON is an administrative dataset containing information on all students enrolled in Dutch secondary and higher education between 2003 and 2015. The data provides information on student-, school- and neighbourhood characteristics. The data offers information on students' gender, socio-economic background[7], ethnicity[8], and age. We also observe numerous elements of students' school career, including the completed level in pre-VET, the average grade on central exams, whether a student received educational support in pre-VET (*lwoo*), whether students were enrolled in senior general secondary education (*havo*) or pre-university education (*vwo*) before completing pre-VET, whether students were tracked or not in the first year of lower secondary education (*brugklas*), and whether students took math, physics, economics or a second language in pre-VET. At the school level, we observe what share of students were enrolled in the theoretical track (*vmbo theorische leerweg*), the economics track, the agriculture track, the STEM track, the healthcare track, or the mixed track. Finally, we observe in which field-of-study students enrol in VET. The aforementioned variables constitute the control variables that are used to estimate equation (1) and (2).

One drawback of the dataset is that we cannot identify participants at the individual level. Therefore, we rely on school-level information on the treatment participation status. In 2014, 294 students participated in the intervention who attended 56 different pre-VET schools.[9] As we observe which schools participants attended, we can calculate the share of students that participated in the intervention in each of the 56 schools. Figure 1 shows frequency statistics on the share of students who participated in the intervention in the 56 schools. We observe that the share of students who participate in the intervention in a pre-VET school varies from 0.3% to 24%.[10] It should be noted that schools with a relatively high share of participants were also subject to promotion of the intervention by the training companies. Participants who had very few peers at the pre-VET school who also participated in the intervention are more likely to

7 The socio-economic indicator is constructed by the Netherlands Institute for Social Research (Sociaal en Cultureel Planbureau) in 2014 for each postal code and is based on the average income in a neighbourhood, the share of individuals with a low income, the share of individuals who are low-educated, and the share of individuals who are unemployed.

8 The data includes binary variables indicating whether at least one of the students' parents is born in Suriname, Aruba, Turkey, or Morocco. Moreover, we observe whether students have a non-Western or Western migrant background and we observe whether students have a first or second generation migrant background.

9 Appendix A shows where the treated schools are geographically located in the Netherlands.

10 Based on the information received from the training companies, the schools that were attended by the participants could be identified at the level of school establishments (6 digit BRIN).

have been informed about the intervention by having visited open days of VET institutes.

Table 1 describes the data. Out of the 126,048 native Dutch male students in our sample, 6.8% attended a treated pre-VET school. Out of the 33,762 male students with a migrant background, 14.7% were enrolled in a pre-VET school in which students participated in the intervention. On average, 43.1% of the Dutch male students enrol into STEM education after completing pre-VET, while only 28.9% of the male students with a migrant background enrol into STEM. The socio-economic status is on average lower for students with a migrant background (-0.83) than for Dutch native students (-0.03). The average final grade on the national exam in pre-VET is 6.6 (on a scale from 1 to 10) for native Dutch students and 6.4 for students with a migrant background. Students are on average 15 to 16 years old when they are enrolled in the final year of pre-VET. Moreover, a larger share of native Dutch male students took mathematics (90.8%) and physics (53.8%) in pre-VET compared to students with a migrant background (86% and 35.1, respectively). In contrast, a larger share of students with a migrant background took economics (63.3%) in pre-VET than native Dutch students (51.8%). The majority of students attend the highest track in pre-VET, the theoretical track (*vmbo theoretische leerweg*). The average share of Dutch native students attending the theoretical track is 42% and 35.8% for students with a migrant background. Finally, Table 1 shows that the average share of native Dutch students who were enrolled in the STEM track in pre-VET is 24%. For male students with a migrant background, the average share of students enrolled into a STEM track in pre-VET is 22.1%.

Table 1 **Descriptive statistics**

	Native Dutch male students					Male students with a migrant background				
	Observations	Mean	SD	Min	Max	Observations	Mean	SD	Min	Max
Treatment school	126,048	0.068	0.252	0	1	33,762	0.147	0.354	0	1
Enrolment into STEM	126,048	0.431	0.495	0	1	33,762	0.289	0.453	0	1
Socio-economic status indicator	126,048	-0.029	1.027	-8.193	2.933	33,762	-0.841	1.541	-8.193	2.933
Student with additional support	126,048	0.217	0.412	0	1	33,762	0.280	0.449	0	1
Grade point average	126,048	6.554	0.452	5.5	9	33,762	6.440	0.422	5.5	8.7
Student attended havo	126,048	0.077	0.267	0	1	33,762	0.057	0.232	0	1
Student attended vwo	126,048	0.005	0.069	0	1	33,762	0.004	0.064	0	1
Student attended brugklas	126,048	0.334	0.471	0	1	33,762	0.308	0.462	0	1
Age final year pre-VET	126,048	15.462	0.591	14	20	33,762	15.649	0.682	14	20
Student took mathematics	126,048	0.908	0.289	0	1	33,762	0.860	0.347	0	1
Student took physics	126,048	0.538	0.499	0	1	33,762	0.351	0.477	0	1
Student took economics	126,048	0.518	0.500	0	1	33,762	0.633	0.482	0	1
Student took second language	126,048	0.212	0.408	0	1	33,762	0.217	0.413	0	1
Level of education in pre-VET										
Vmbo basisberoeps-gerichte leerweg	126,048	0.073	0.260	0	1	33,762	0.035	0.184	0	1
Vmbo kaderberoeps-gerichte leerweg	126,048	0.216	0.411	0	1	33,762	0.307	0.461	0	1
Vmbo gemengde leerweg	126,048	0.291	0.454	0	1	33,762	0.300	0.458	0	1
Vmbo theoretische leerweg	126,048	0.420	0.494	0	1	33,762	0.358	0.479	0	1
Educational sector in pre-VET										
Percentage of students in theoretical track	126,048	0.425	0.371	0	1	33,762	0.392	0.370	0	1
Percentage of students in economics track	126,048	0.124	0.157	0	1	33,762	0.180	0.201	0	1
Percentage of students in agriculture track	126,048	0.083	0.255	0	1	33,762	0.029	0.152	0	1
Percentage of students in STEM track	126,048	0.240	0.264	0	1	33,762	0.221	0.253	0	1
Percentage of students in healthcare track	126,048	0.029	0.052	0	1	33,762	0.032	0.058	0	1
Percentage of students in mixed track	126,048	0.098	0.188	0	1	33,762	0.145	0.229	0	1
Migrant background										
Suriname						33,762	0.124	0.330	0	1
Aruba						33,762	0.053	0.225	0	1
Turkey						33,762	0.200	0.400	0	1
Morocco						33,762	0.165	0.372	0	1
Non western migrant background						33,762	0.206	0.405	0	1
Western migrant background						33,762	0.249	0.433	0	1
First generation migrant						33,762	0.166	0.372	0	1
Second generation migrant						33,762	0.833	0.373	0	1

5. Results

Before turning to the main results, we show the results of the analysis of leads and lags. Table 2 shows that Native Dutch male students in treated and untreated schools were behaving similarly before the introduction of the intervention in 2014-15. The coefficients are small and not statistically significant. For students with a migrant background, the interaction between the 2011-12 indicator and the treatment indicator is significant. This implies that the trend in terms of STEM enrolment is only parallel in the two years prior to the introduction of the intervention. Therefore, as a robustness check, we will apply propensity score matching to balance the control and treatment group on a set of characteristics that influence the probability of receiving the treatment (see Section 6).

Table 2 Difference-in-differences with leads and lags

	Native Dutch male students	Male students with a migrant background
Treated school * 2011-12	-0.000 (0.016)	0.042** (0.020)
Treated school * 2012-13	-0.013 (0.015)	0.001 (0.017)
Treated school * 2014-15	-0.010 (0.014)	0.021 (0.019)
Controls	X	X
Treatment fixed effect	X	X
Year fixed effects	X	X
Number of clusters	888	877
Observations	126,048	33,762
R-squared	0.230	0.207

Notes: The reference year is 2013-14. Asterisks indicate significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The standard errors are clustered at the school level.

Table 3 presents the results of the *DiD*-estimates. Models 1a, 1b, 3a and 3b in Table 3 show the *DiD*-estimates with a binary indicator for having received the treatment. Models 2a, 2b, 4a and 4b present the *DiD*-estimates with a continuous indicator for having received the treatment. Model 1a, 2a, 3a and 4a show the results without control variables and models 1b, 2b, 3b and 4b present the estimates when all control variables are included. The estimates presented separately for native Dutch students (models 1a, 1b, 2a and 2b) and students with a migrant background (models 3a, 3b, 4a and 4b). Given that in some schools, only few students participated in the intervention (Figure 1), our preferred specification includes the continuous treatment indicator.

Table 3 shows that native Dutch students who attended a treatment school are 0.6%-points less likely to enrol into STEM education than students who attended an untreated school (model 1b). However, the difference is not statistically different from zero. Similarly, a 1%-point increase in the share of students that participated in the intervention in students' pre-VET school does not increase native Dutch students' likelihood to enrol into STEM (model 2b). Hence, the results in model 1b cannot be explained by the fact that many schools had a very small percentage of students who participated in the intervention (Figure 1).

For students with a migrant background who attended a treated school, the likelihood to enrol into STEM education is 0.9%-points larger than for students who have attended an untreated school (model 3b). However, the effect is statistically insignificant. Only model 4b provides a significant ITT estimate. The continuous indicator shows that a 1%-point increase in the share of students that participated in the intervention in the pre-VET school, increases the likelihood that students with a migrant background enrol into STEM education with 0.6%- points.

6. Robustness

As a robustness check, we additionally account for differences in background characteristics between students in treated and untreated schools by applying propensity score matching. The matching technique allows us to balance the control and treatment groups with respect to characteristics that could simultaneously affect the likelihood that a student participates in the intervention and enrols into STEM education. In order to accommodate the conditional independence assumption (*CIA*), we match students in treated and untreated schools on observed pre-treatment characteristics.

The CIA assumption states that, conditional on the observable pre-treatment variables X_{ij}, participation in the intervention is independent of the potential outcomes (Angrist and Pischke 2008). We apply the Nearest Neighbour (NN) one-to-one propensity score matching technique and perform 1,000 replications with random sorting of the data.[11] Due to the richness of the data, we have a large pool of potential control observations. This is in favour of the NN-matching of students without replacement. We choose for a caliper close to zero (i.e., 0.001) in order to guarantee that the differences between the propensity scores of treated and untreated students are small. The students in treated schools are matched to students in untreated schools based on all available pre-treatment variables (see Section 4).[12]

The average estimated ITT for native Dutch students when using the binary treatment indicator is 0.1%-points (0.001) and has a standard deviation of 0.001. The 95% confidence interval [min: -0.001., max: 0.0003] contains zero. We conclude that the ITT estimate is qualitatively similar to the small and insignificant effect obtained in the unmatched sample (-0.006). The average estimated ITT obtained after NN-matching when using the continuous treatment indicator is -0.01%-points (-0.0001) with a standard deviation of 0.00004. This is qualitatively similar to the estimate obtained when using the continuous treatment indicator in the unmatched sample (-0.001). The size of the obtained estimate is almost negligible. Hence, the findings suggest that the intervention did not affect native Dutch students' probability to choose for STEM.

The average estimated intent-to-treat effect ITT for students with a migrant background when using the binary treatment indicator is -1.5%-points (-0.015) with a standard deviation of 0.002. The ITT estimate obtained in the unmatched sample is qualitatively different (0.005) and, therefore, not robust. In contrast,

11 The randomization process ensures that our estimates will not depend on the order in which observations are matched.

12 Figures of the empirical distribution of the estimated intent-to-treat (ITT) effects based on the 1,000 samples that are obtained after NN-matching are available upon request from the authors.

Table 3 Difference-in-differences estimates

	Native Dutch male students				Male students with a migrant background			
	Model 1a	**Model 1b**	**Model 2a**	**Model 2b**	**Model 3a**	**Model 3b**	**Model 4a**	**Model 4b**
Treated school * Time indicator	-0.019 (0.017)	-0.006 (0.012)			-0.008 (0.019)	0.009 (0.018)		
Share of male participants in school * Time indicator			-0.002 (0.002)	-0.001 (0.002)			0.005 (0.003)	0.006** (0.002)
Treatment fixed effect	X	X			X	X		
Share of male participants in school			X	X			X	X
Time fixed effect	X	X	X	X	X	X	X	X
Control variables								
Socio-economic status indicator		X		X		X		X
Student with additional support		X		X		X		X
Grade point average		X		X		X		X
Student attended havo (ref. category)		X		X		X		X
Student attended vwo		X		X		X		X
Student attended brugklas		X		X		X		X
Age final year ***pre-VET***		X		X		X		X
Student took mathematics		X		X		X		X
Student took physics		X		X		X		X
Student took economics		X		X		X		X
Student took second language		X		X		X		X
Level of education in pre-VET		X		X		X		X
Educational sector in pre-VET		X		X		X		X
Migrant background								
Suriname						X		X
Aruba						X		X
Turkey						X		X
Morocco						X		X
Non western migrant background						X		X
Western migrant background						X		X
First generation migrant (ref. category)						X		X
Second generation migrant						X		X
Number of clusters	888	888	888	888	877	877	877	877
Observations	126,048	126,048	126,048	126,048	33,762	33,762	33,762	33,762
R-squared	0.000	0.230	0.002	0.230	0.002	0.208	0.001	0.208

Notes: Asterisks indicate significance levels:
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The standard errors are clustered at the school level.

the ITT estimates after NN-matching are highly comparable to the estimates obtained on the unmatched sample when a continuous indicator is used. The average estimated ITT for students with a migrant background when using the continuous treatment indicator is 0.5%-points (0.005) and has a standard deviation of 0.0002. The range of estimates does not include zero [min: 0.005, max: 0.007]. We conclude that the estimates obtained after NN-matching are qualitatively similar to the estimate obtained in the unmatched sample (0.006). Because our preferred specification contains the continuous treatment indicator, we conclude that the intervention has had a small but significant effect on the likelihood that students with a migrant background enrol into STEM.

7. Conclusion and discussion

Although the demand for STEM graduates has been increasing in most European countries, the share of students graduating from STEM in VET has declined in recent years. Despite the fact that there are numerous studies examining the effectiveness of interventions aimed at increasing enrolment rates into STEM education, none of these studies focused on actual enrolment rates into STEM. Moreover, most studies focus on interventions that are designed to motivate students to enrol into STEM in higher education. This paper evaluates the effectiveness of a five-day intervention designed for pre-VET students with the aim to increase enrolment into STEM in VET.

Our findings suggest that the intervention had no effect on native Dutch male students. A potential explanation for why the intervention had no significant effect on native students is that the intervention was targeted at pre-VET schools in which a large share of students were enrolled in a STEM track. These students might have enrolled into STEM even in absence of the intervention. In contrast, our findings show that the five-day programme had a small, but significant effect on male students with a migrant background. A 1%-point increase in the share of students at the pre-VET school participating in the intervention significantly increased the likelihood of enrolling into STEM with 0.6%-points.

Both native students as well as students with a migrant background in our study constituted a selective sample of participants. Nonetheless, migrant background students who show an interest in STEM might still be more likely to be in doubt as to whether they should actually enrol into STEM education. Students with a migrant background, as well as their parents, tend to have negative associations with STEM occupations due to the low status in the country of origin (De Koning et al. 2010). Parents of migrant background students in the Netherlands are more inclined to place their children into an economics or business programme as office jobs are perceived to have a higher occupational status (De Koning et al. 2010).

Moreover, migrant background students are less likely to believe that they have the ability to successfully complete a STEM programme (MacPhee et al. 2013). Hence, the discrepancy between students' beliefs and their actual preferences and ability is likely to be larger for migrant students. The potential of the intervention to update students' beliefs about their ability and preferences by experiencing STEM occupations through hands-on-activities is likely to have been larger for migrant background students (Kuijpers and Meijers 2009; De Koning et al. 2010). In addition, migrant students and their parents are less well-informed about the labour market perspectives of STEM programmes (De Koning et al. 2010). The larger information gap among students with a migrant background might be another explanation for why the intervention only had a significant effect on migrant students. Earlier research shows that students from lower socio-economic backgrounds, who also have a relatively large information gap, tend to be more sensitive to labour market information (Hoxby and Turner 2013; Wiswall and Zafar 2015b). Future research must point out whether these potential explanations are in fact the mechanisms that explain why the intervention only had an effect on a selective group of migrant students.

Based on our findings, we can draw several policy implications and provide guidelines for future research. The intervention is likely to have had no significant effect on native students, and only a small effect on migrant students, due to the selective sample of participants. Hence, future interventions should be targeted at students who do not already show a clear interest in STEM or who are in doubt as to whether STEM matches their preferences and ability. Because students choose to enrol into a specific track in the third year of pre-VET, future interventions should trigger students' interest for STEM at an earlier stage in their educational career (De Philippis 2017). Apart from increasing enrolment into STEM education, the intervention also aimed at improving the match between STEM study programmes and students who were already interested in STEM. While our dataset does not enable us to observe treated students in the second year of VET, it is reasonable to expect that the intervention increased the likelihood that treated students complete the STEM study programme in which they enrolled after the intervention. Future research should point out if this is actually the case. Finally, the five-day programme ideally also increases the likelihood that participants end up in STEM jobs on the labour market. Matching vacancies for STEM jobs with STEM graduates remains a challenge in the Netherlands as an increasing share of STEM graduates end up in jobs that are unrelated to the attended field-of-study (ROA 2017).

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Appendix A. Geographical distribution of treated and untreated schools