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The vocational impact of educational programs on youth labor market integration

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A R T I C L E I N F O

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A B S T R A C T

Much research is done on the impact of vocational education and training (VET) systems on youth's transition from school to work. However, this research treats vocational education within countries as a homogeneous entity and as if the 'vocational effect' equally applies to the entire VET system, while nuanced insights in the within-country heterogeneity of the vocational impact are remarkably scattered. This study attempts to open this black box by investigating to what extent the vocational specificity of educational programs has a positive impact on having a paid job and experiencing immediate job entry and job matching among recently graduated VET school-leavers in the Netherlands. Additionally, we theorize and test the moderating role of regional youth unemployment rates. Unique to this study are the two vocational measurements of programs, which were obtained by assessments of professionals involved in the programs (e.g. teachers, managers, education coordinators). Using data from the VET survey and VET expert survey – covering 114 educational programs between 2010 and 2014 – our multilevel models generally show a positive vocational impact of programs on youth's labor market opportunities. Unexpectedly, the vocational impact does not vary with regional youth unemployment rates. We reflect on our findings within the context of current school-to-work literature.

1. Introduction

A successful transition from education to work is crucial for young people's future employment opportunities and moreover a good predictor of other adulthood transitions (Barbieri, Cutuli, & Passaretta, 2016; Protsch, 2017; Scherer, 2005). Previous empirical research on school-to-work transitions reaches the general conclusion that the initial transition from school to work runs more smoothly among young people in countries with an elaborate vocational education and training (VET) system (Barbieri et al., 2016; Breen, 2005; De Lange, Gesthuizen, & Wolbers, 2014; Levels, Van der Velden, & Di Stasio, 2014; Van de Werfhorst, 2011a; Wolbers, 2007). Moreover, vocational qualifications appear to smoothen the transition most in countries with a strong VET system, as seen for example in German-speaking countries and the Netherlands (Barbieri et al., 2018; De Lange et al., 2014; Raffe, 2008,2014). This line of research thus indicates that the vocational specificity of educational programs is "the main mechanism through which vocational education influences [youth's] labor market outcomes" (Forster & Bol, 2018, p. 177).

Yet, these comparative studies theoretically and empirically disregard possible existing variations of the vocational specificity *between* educational programs *within* vocational education. The present study aims to provide more nuanced insights in the vocational impact on youth's labor market chances by focusing on differences between VET programs rather than between VET systems. In research on school-to-work transitions it is quite common to investigate the specificity of education systems dichotomously (vocational vs. general) or as the share of students enrolled in vocational education (or dual) systems. This, however, treats vocational education within a country as if it is a homogeneous entity, and as if the vocational effect under investigation equally applies to the entire VET system (see also Raffe, 2014, p. 182). Furthermore, this line of research generally assumes that if a VET system is classified as highly vocationally specific, all programs within that VET system lead to highly specific skills. This is also reflected in the commonly used measurements in the literature. Following Bol et al. (2019), DiPrete et al. (2017), Forster and Bol (2018), and Vogtenhuber (2014), we argue that the specificity of educational programs is gradual and that there can be substantial heterogeneity in specificity *between* programs *within* VET. Some vocational programs, like a car mechanic program, might indeed teach very specific occupational skills, whereas other programs, for instance marketing and communication programs, might in fact yield rather generic skills even though they are also classified as vocational programs.

To this end, our first research question reads: *To what extent does the vocational specificity of educational programs in VET promote school-leavers' labor market integration?* Or stated differently, do school-leavers from more specific programs in VET experience better labor market

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outcomes than school-leavers from less specific programs in VET? Four common indicators of youth labor market integration are examined: having a paid job, immediate job entry after graduation, and experiencing a horizontal job match (i.e. matching to the field of education) or a vertical job match (i.e. matching to the level of education). We investigate our research question within the context of vocational education in the Netherlands ('MBO' in Dutch), which lends itself well for the purpose of our study because it is characterized by a high degree of heterogeneity, as is more often the case in highly stratified and vocationally specific educational contexts (Vogtenhuber, 2014).

We attempt to open the black box of within-country heterogeneity in the vocational impact of educational programs on youth's labor market integration in three important ways. First, with unique Dutch data we have at hand we advance on a few available similar studies targeting (vocational) program effects (Bol et al., 2019; Coenen, Heijke, & Meng, 2015; DiPrete et al., 2017; Forster & Bol, 2018; Van der Velden & Wolbers, 2007; Vogtenhuber, 2014). We use two measures of the vocational specificity of educational programs, obtained through assessments by professionals involved in the programs (e.g. teachers, managers, and education coordinators). In these aforementioned studies, the vocational specificity of programs is measured through the observed number of occupational positions a single educational program is linked to. The narrower the distribution of school-leavers over various occupational positions (or the less occupational variation a program has), the more vocationally specific the program is considered to be. Not only are these measures less directly linked to the curricular design and content of the educational program, they are also measured by and therefore inextricably linked with the labor market outcome variables. By contrast, the measures we use here determine the vocational specificity based on characteristics of the educational program itself.

Moreover, we examine the vocational impact over and above the influence of other important educational observables (e.g. educational level within VET, and average graduation grade) and individual characteristics (e.g. self-rated specific and generic skills, and parental educational background). Previous research has encouraged future studies to better control for factors both related to school-leavers' educational decisions and their labor market outcomes, as they were only able to do so to a limited extent (see Forster & Bol, 2018, p. 189; Vogtenhuber, 2014, p. 380). By taking these confounding factors into account, we thus aim to provide a closer investigation of the vocational impact of educational programs.

Second, by focusing on differences in youth's labor market outcomes *between* educational programs this paper tests well-known theories of queuing and networks. Although these micro theories have frequently been tested in comparative research in which the micro-mechanisms are applied to explain possible macro-level (or cross-national) differences (see Raffe, 2014), it is of dire interest to test these mechanisms on the level in which they are primarily expected to operate. Up to now, surprisingly little is known about the extent to which these well-established theories might explain possible differences in youth labor market integration between educational programs. Because of the more direct conceptualization and measurement of the vocational specificity of educational programs we use, we provide more direct tests of these theories than similar prior studies (e.g. Forster & Bol, 2018; Vogtenhuber, 2014). Previously, vignette studies on employers' hiring behavior have tested the impact of these actual micro mechanisms on labor market chances quite directly and adequately (e.g. Di Stasio & Van de Werfhorst, 2016; Protsch & Solga, 2015), but these were naturally more focused on differences (in educational and individual characteristics) between job seekers and not so much on differences between educational programs.

Third, so far little is known to what extent macro-economic conditions influence the relationship between the specificity of educational programs and youth's integration into the labor market. A negative aspect of vocationally specific programs is that they might limit mobility across occupations (e.g. Coenen et al., 2015; Korpi et al., 2003). Thus, when demand is low, school-leavers from these programs may be exposed to higher risks of unemployment and downward mobility (Protsch & Solga, 2016). In other words, the positive impact of vocationally specific programs might actually turn into a penalty when, for instance, regional unemployment rates are high. Given that educational qualifications are more binding in tightly regulated and highly segmented labor markets (Scherer, 2004), it would be particularly interesting to examine this within such a context, as is the case in the Netherlands. Our second research question therefore reads: *To what extent do regional unemployment rates influence the positive impact of the vocational specificity of educational programs in VET on school-leavers' labor market integration?*

2. Theory

With respect to our first research question, we draw on two theoretical approaches to explain possible within-country heterogeneity in the vocational impact of VET programs. We consider queuing and network mechanisms as explanations for the following supposition: more specific programs provide a smoother transition into the labor market for school-leavers than less specific programs. These two mechanisms are known to be very hard to disentangle empirically (see Di Stasio & Van de Werfhorst, 2016; Bills, 2003; Van de Werfhorst, 2011a) and this study is no exception. We therefore discuss both theoretical approaches and their assumptions about which mechanisms underlie the vocational impact, before formulating our hypotheses.

We can distinguish and take into account the role of school-leavers' human capital (Becker, 1964), which concerns individuals' level of skills that can to some extent be observed by employers. The two other mechanisms run through program characteristics, as they concern either signals sent through educational qualifications or networks that exist between schools or graduates and employers. Thus, to rule out that program effects are not, in fact, effects of one's acquired skills, school-leavers' levels of self-rated job-specific and generic skills (discussed in data below) are taken into account.

2.1. Signaling

The *queuing* approach refers to a cluster of theories explaining *why* education increases youth's labor market chances, which argues that job-seekers use education to send *signals* to employers (Spence, 1973), whereas employers use education as a screening device (Arrow, 1973) that provides information about job-seekers' trainability, productive capacity and other unobserved qualities, such as commitment, perseverance and motivation. In addition, Thurow (1975) emphasizes that employers use signals to screen for applicants that require the least (additional) training costs. This screening process based on educational signals is a cheap and therefore commonly adopted method for employers to obtain more information about applicants when direct information about their actual level of skills is limited, incomplete or not observable to them. The latter is especially the case with regard to new labor market entrants that have no prior employment experience nor references from previous employers (Brzinsky-Fay, 2017, p. 348). What is most important here is that it depends strongly on the educational and labor market context whether educational qualifications send clear and informative signals.

In the Netherlands, the education system is highly stratified and standardized, and VET ('MBO' in Dutch) is, in general, highly vocationally oriented with strong linkages to the labor market (Iannelli & Raffe, 2007; Raffe, 2008; Van der Velden & Wolbers, 2007). Because of this high level of educational tracking (i.e. stratification) and highly standardized educational input (i.e. what is taught) and output (i.e. qualifications obtained against external, nationwide standards), educational qualifications in this context signalclear and reliable information to employers about job-seekers' level of skills, trainability and potential productivity (Bol & Van de Werfhorst, 2011; Levels et al., 2014; Scherer, 2005). The more valid the signals of educational credentials are in conveying information about the real qualifications and skills of school-leavers, the more weight is given to them during recruitment processes (Scherer, 2005, p. 429). These institutional features in the Dutch education system thus allow employers to rely more strongly on educational signals compared to more weakly stratified and generalist education systems, such as the UK (see also Di Stasio & Van de Werfhorst, 2016).

Furthermore, the strong vocational specificity of Dutch VET equips students with a strong occupational specialization for jobs that are related to their educational program. Hence, the more vocationally specific a program is, the clearer and more informative the signals are to employers about school-leavers' level of occupation-specific skills and potential productivity (Bol & Van de Werfhorst, 2011, p. 122; Breen, 2005, p. 126).

Finally, active involvement of employers in the curricular design of educational programs increases the signaling power of educational qualifications (Breen, 2005, p. 126; Iannelli & Raffe, 2007, p. 50). These two features – i.e. vocational specificity and institutional linkage – are less distinct than they appear to be, as argued by Breen (2005, p. 126). Programs that are more closely linked to the labor market ensure that the skills taught in educational curricula not only closely reflect skills that are actually in demand by employers (Levels et al., 2014), but employers also have "more direct knowledge of the programs and of the students they recruit" (Iannelli & Raffe, 2007, p. 50). This naturally increases the clarity and credibility of the information sent through signals, and employers' confidence to rely on it (Di Stasio & Van de Werfhorst, 2016; Iannelli & Raffe, 2007; Raffe, 2008). Because programs with more vocationally specific curricula tend to be more strongly embedded in an institutional relationship with the labor market, we expect a close involvement to be most present in these programs

Altogether, it follows that more specific educational programs send more informative and clear signals to employers about job seekers' immediate productivity on entry and potential future productivity than less specific programs (Bol & Van de Werfhorst, 2011; Breen, 2005; Iannelli & Raffe, 2007; Vogtenhuber, 2014). We therefore expect that more specific programs increase school-leavers' chances of being allocated to a paid job and experience a faster entry into the labor market (Scherer, 2005; Wolbers, 2007). Likewise, we expect more specific programs to increase chances for school-leavers to find a job that matches their field and level of education (i.e. horizontal and vertical matching). The specific vocational qualifications increase the amount of information available for employers, helping them to successfully allocate school-leavers to jobs that match their skills (Levels et al., 2014). Generally, the better informed employers are, the lower the chances that job mismatches occur, as they most often occur under imperfect information conditions (Breen, 2005; Levels et al., 2014; Scherer, 2004, 2005; Vogtenhuber, 2014).

2.2. Network mechanisms

Next to signaling, n*etwork mechanisms* may also play an important role through the vocational specificity and institutional linkages of educational programs. Network theories (Rosenbaum et al., 1990) suggest that students might capitalize on contact with employers by making use of the information and influence employers have. Through contact between programs and students on the one hand and employers on the other hand, employers may allocate school-leavers to jobs in their own firms, offer school-leavers help in finding a job or help them being allocated to jobs. This can increase school-leavers' chances to enter a job more quickly after successful completion of the attended program (Breen, 2005; Iannelli & Raffe, 2007). We expect that school-leavers from more specific programs are better able to establish contact with employers and therefore benefit more from it, because these programs tend to have more and better ties with employers (i.e. closer linkages).

Next, networks can also facilitate students' chances to find a matching job at the end of their training program (Levels et al., 2014, p. 345; Scherer, 2005). School-leavers from more specific programs may obtain more and better information via employers about available jobs and this would in turn improve their chances of finding *a better suited job* (i.e. one that matches their level and field of education more closely). Conversely, programs and graduates with fewer or less strong ties to employers may have to do with less information and graduates from these programs may therefore be more likely to end up accepting jobs that are less fitting to their educational background

Moreover, employers may favor those applicants that have a preexisting relation with the firm. One reason for this preference is that employers are able to prescreen their actual level of (job-specific) skills and productivity, and assess firsthand whether they are fit for the job (Di Stasio & Van de Werfhorst, 2016). Another reason might be that employers have already invested time in their training in order to improve their firm-specific human capital and productivity. This preference may thus increase school-leavers' chances to continue to work within firms where they completed their workplace training (Levels et al., 2014), which in turn increases their chances of having a paid job, experiencing immediate entry, and a matching job.

To summarize, because of clearer signals of productivity and more possible future employers in their social network, VET school-leavers from more specific programs experience better labor market opportunities than those from less specific programs. Concretely, our first hypothesis reads as follows:

> *The morespecific theprogram, the higherschool-leavers'chancesof having a paid job (H1a), experiencing immediate job entry (H1b) and horizontal (H1c) and vertical (H1d) job matching.*

2.3. Vocational impact under different macro-economic conditions

Moving on to our second research question, which asks whether the impact of the vocational specificity of programs on youth's labor market integration depends on and varies with macro-economic conditions. In highly specific programs, the acquisition of specific skills provides students with a strong specialization for and optimal preparation in a particular field of occupation, which is appealing for both students and employers (Hanushek, Schwerdt, Woessmann, & Zhang, 2017). We have argued how more specific programs may lead to increased labor market chances. However, one could also argue that stronger occupational specialization in educational programs might turn into a disadvantage when aggregate unemployment rates are high and labor market demands low. Under such circumstances, school-leavers from specific (or specialized) educational programs may prove to be less flexible on the labor market compared to those from less specific programs (Borghans & de Grip, 2000; Hanushek et al., 2017). While graduates from specific programs have acquired occupationally specific skills that are applicable in a small(er) subset of occupations, their counterparts from less specific programs have acquired skills that are more applicable to a wider set of occupations (Borghans & de Grip, 2000; Coenen et al., 2015; Hanushek et al., 2017). Consequently, and given the fact that VET school-leavers are generally oriented towards the local labor market, it can be assumed that when regional unemployment rates are higher, recent graduates from more specific programs can less easily divert to other occupations compared to those from less specific programs (Coenen et al., 2015; Korpi et al., 2003; Reimer, Noelke, & Kucel, 2008). Thus, school-leavers from more specialized programs might less quickly find employment or jobs that match their level and field of education compared to school-leavers from less specific programs, especially when first entering the labor market. In other words, specific programs may be more advantageous in regions with lower unemployment rates. Our second hypothesis

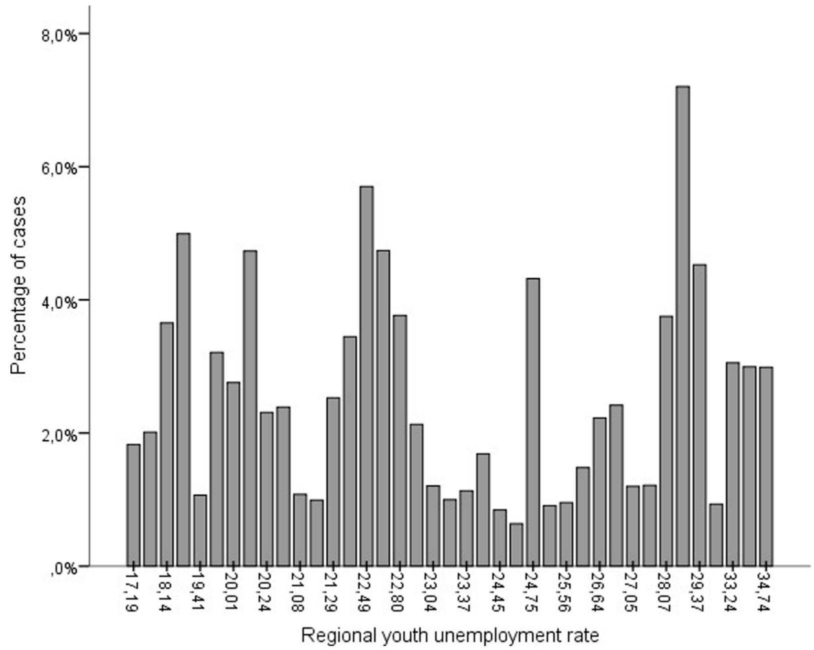

Fig. 1. Percentage of cases per regional youth unemployment rate in the sample (N = 15,571).

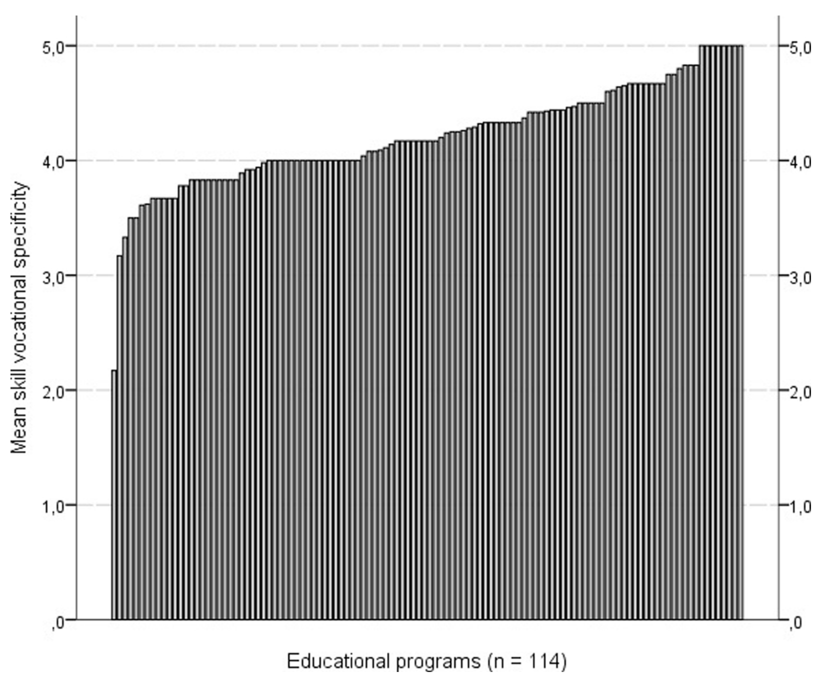

Fig. 2. The mean skill vocational specificity of each VET program (N = 15,571).

therefore reads:

The positiveimpact of thespecificity ofprogramsonschool-leavers' likelihood of having a paid job (H2a), experiencing immediate job entry (H2b) and horizontal (H2c) and vertical job matching (H2d) is smaller when the regional unemployment rate is higher.

3. Data

3.1. Data of VET school-leavers

We empirically test our hypotheses with cross-sectional data from the annual VET survey conducted in the Netherlands by the Research Centre for Education and the Labor Market (ROA) of Maastricht University, collected in the period 2011-2015. The main aim of the survey is to provide insight into the transition from school to work (or continuous education) among graduated school-leavers from upper secondary VET in the Netherlands. For this reason, they are questioned one and a half years after school-leaving by means of either the written or online version of the questionnaire. The survey collects both retrospective information about school-leavers' educational background and information about their educational and labor market activities at the time of the survey. An advantage of using data on recent graduates is that their labor market outcomes are more directly affected by their education (Van de Werfhorst, 2011b).

The main focus of our paper is to analyze the initial school-to-work

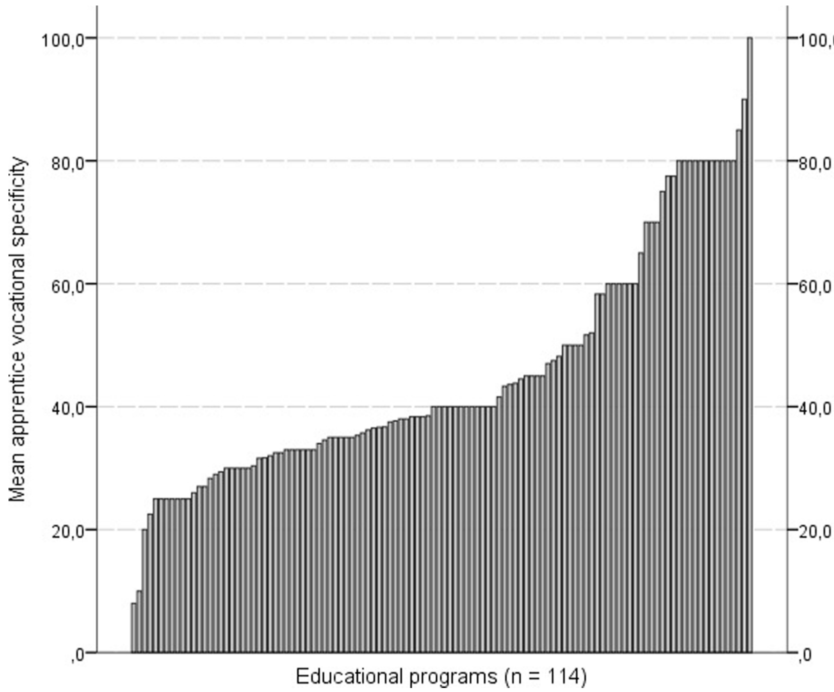

Fig. 3. The mean apprentice vocational specificity of each VET program (N = 15,571).

transition among recently graduated school-leavers from upper secondary VET. Because of this, we are only interested in school-leavers, who at the time of the survey were between the ages of 16 and 27, no longer studied, had not obtained an additional (higher) degree, and were not self-employed or working freelance. Moreover, we focus on school-leavers from VET levels 2, 3, and 4, and thereby exclude VET levels 1 and 4+ (specialist training). According to the widely used International Standard Classification of Education (ISCED), only the diplomas of the selected levels are internationally comparible to upper secondary VET (i.e. ISCED 3). Finally, we selected educational programs with 15 or more school-leavers (n = 225 programs) in order to have sufficient variation within the programs. The data sample relevant for our study therefore consisted out of 21,212 school-leavers.

3.2. Data of VET experts involved in programs

We enriched the individual school-leaver data with two measurements referring to the vocational specificity of educational programs. We obtained this information from a survey held among professionals involved in the VET programs. We will refer to this survey as the VET expert survey ('CGO-monitor' in Dutch). The aim of this survey is to measure the objectives of competency-based (or skill-based) vocational education, which relate to the provision of vocational and generic competencies within programs (Van der Meijden, Van den Berg, & Román, 2013). The expert survey was carried out by the Dutch Centre for Expertise in Vocational Education and Training ('ecbo' in Dutch) on behalf of the Dutch Ministry of Education. We use expert data from 2011, the most recently collected wave of this survey. Because the Netherlands has a highly standardized education system (Van der Velden & Wolbers, 2007) and no major structural changes took place in the VET-curricula between 2011 and 2015, this information can be assumed to form an accurate reflection of programs' features for the entire period under study.

The questionnaire was directed at contact persons (coordinators) of educational programs of publicly funded VET institutions in the Netherlands (response rate: 48 percent). Respondents had to have one of the following positions within educational programs: coordinator, teacher, or manager. They often had overlapping functions (e.g. being a teacher and a team coordinator). Some of the respondents were involved in more than one training program, but had to fill out the survey for the program they were most involved with (i.e. for which they were employed the most hours per week).

The expert dataset consists of a total of 947 professionals. However, not all educational programs were present in both the expert and school-leaver dataset, which resulted in a remainder of 119 programs in both datasets. The expert data was thereby reduced to 380 professionals. Based on experts' assessments, two measurements were conducted for the vocational specificity of the programs. Due to missing values on these measurements (2.2 percent), only a total of 114 programs among 15,912 school-leavers remained in our final analytical sample. While combining these two datasets has led to the loss of a number of respondents, it gives us the unique opportunity to analyze the vocational impact of programs on school-leavers' labor market chances.

3.3. Regional unemployment data

Lastly, we also enriched the school-leaver data with information on yearly regional youth unemployment rates which we obtained from Statistics Netherlands (2018a). The Netherlands can be divided into 40 regional areas, also known as COROP regions. One relatively small regional area ('Delfzijl and area') had few respondents, so we combined it with the neighboring area ('remainder of Groningen'), which ultimately resulted in 39 COROP areas. More information about the specific operationalization follows below.

4. Measurements

4.1. Labor market outcomes

Having a paid job at the time of the survey was measured with the question: "Do you have a paid job at this moment?". Respondents could answer with yes (1) or no (0). As indicated above, the analytical sample consisted of 15,912 school-leavers and we refer to this sample as the 'total sample', as it includes both employed and unemployed individuals.

Table 1
Descriptive statistics of all (pre-standardized) variables for both samples.
Source: VET survey (2011–2015) and VET expert survey (2011).

			Total sample (N = 15,571		Employed sample (N = 11,678)	
	Min.	Max.	Mean	Std. dev.	Mean	Std. dev.
Paid job	0	1	0.89	0.32		
Immediate entry	0	1			0.80	0.40
Horizontal job match	0	1			0.70	0.46
Vertical job match	0	1			0.74	0.44
Program level						
Vocational specificity of program: skills and knowledge	2.17	5.00	4.30	0.36	4.31	0.36
Vocational specificity of program: apprenticeship training	8.00	100	43.85	14.28	44.12	14.37
VET level						
Level 2 (= ref.)	0	1	0.16	0.37	0.13	0.34
Level 3	0	1	0.28	0.45	0.28	0.45
Level 4	0	1	0.56	0.50	0.59	0.49
Educational sector						
Economics (= ref.)	0	1	0.32	0.47	0.30	0.46
Agriculture	0	1	0.02	0.13	0.02	0.13
Technology	0	1	0.18	0.38	0.18	0.38
Health	0	1	0.28	0.45	0.30	0.46
Social work	0	1	0.20	0.40	0.20	0.40
Region level						
Regional youth unemployment rate	17.19	34.74	24.39	4.55	24.24	4.51
Individual level						
Female	0	1	0.69	0.46	0.69	0.46
Age	16	27	21.85	1.78	21.83	1.75
Migration background						
Native Dutch (= ref.)	0	1	0.86	0.35	0.89	0.32
Western migration background	0	1	0.05	0.21	0.04	0.20
Non-western migration background	0	1	0.10	0.30	0.07	0.26
Parental educational background						
Lower educated (= ref.)	0	1	0.21	0.41	0.22	0.41
Intermediate educated	0	1	0.40	0.49	0.45	0.50
Higher educated	0	1	0.25	0.43	0.27	0.45
Parental missing	0	1	0.14	0.34	0.06	0.24
Year of graduation						
2010 (= ref.)	0	1	0.08	0.27	0.09	0.28
2011	0	1	0.07	0.25	0.07	0.26
2012	0	1	0.40	0.49	0.40	0.49
2013	0	1	0.07	0.26	0.07	0.26
2014	0	1	0.38	0.48	0.37	0.48
Average graduation grade	6.00	8.50	7.33	0.53	7.35	0.53
Specific skills	1	5			3.88	0.64
Generic skills	1	5			3.77	0.66

The remaining three labor market outcomes – immediate labor market entry,[1] and horizontal and vertical job matching – were solely measured for employed individuals (14,091 school-leavers out of the total sample). *Immediate labor market entry after graduation* was measured using the question whether (1) or not (0) the respondent was employed after finishing VET. *Horizontal job matching* was measured by asking respondents whether (1) or not (0) their own or a related field of study was required for their current job. *Vertical job matching* was measured in a similar way and indicates whether (1) or not (0) school-leavers have a current job that matches their own level of education. After excluding cases with missing values on our dependent variables, the sample was reduced to 13,243 respondents. We will call this sample the 'employed sample' for the sake of clarity.

4.2. Regional unemployment rate

As mentioned earlier, we obtained information on yearly regional youth unemployment rates among all 15- to 27-year-olds from Statistics Netherlands (2018a). These regional rates were linked to the regional location of respondents' schools. In 67.1 percent of the cases, the regional location of the school was also the region where school-leavers lived. As a robustness check, we ran the models with the region of respondents' place of residence during their last year of the program. These results are similar to the results presented in the paper and are available upon request.

Furthermore, the rates were averaged over the five sampling years and then standardized. Overall, the differences in rates between our sampling years are not big. For only three of the 39 regions these rates differed strongly between years (6–7%-points). We conducted additional analyses with yearly unemployment rates, which we discuss below. Due to missing information on the regional location of the school for some respondents some cases had to be excluded (.1 percent in both samples). Fig. 1 depicts the pre-standardized distribution of the averaged regional youth unemployment rates, ranging from 17 to 34 percent.[2]

4.3. Program characteristics

First, the *vocational specificity of educational programs* in terms of *amount of vocational skills and knowledge* was measured in the VET expert survey among professionals involved in the programs. The following six items were used to measure the degree to which a program is vocationally specific (on a 5-point Likert response scale, ranging from very inadequate [1] to more than sufficient [5]): 'To what extent do you think the educational program trains students to become qualified trades workers?', 'To what extent do students in your program develop vocational knowledge?', 'To what extent do students in your program develop vocational skills?', 'To what extent do students in your program develop a professional attitude?' and 'To what extent do students in your program develop competencies to carry out core tasks of the profession?'. We averaged the scores and created a standardized scale (Cronbach's alpha = .89). Fig. 2 presents the pre-standardized distribution, showing considerable variation (around 33 percent) between programs on this scale.

Second, VET professionals also answered the following question related to the *vocational specificity of educational programs* in terms of *apprenticeship training (on-the-job experience)*: 'What is (approximately) the total percentage of time spent in apprenticeships training at firms during the entire program?'. The scores were subsequently

[1] Immediate labor market entry was actually also measured among unemployed school-leavers. However, because we wanted to take into account the confounding role of specific and generic skills, which was only measured among employed individuals, we decided to present these findings instead. We did run the models on the total sample, which showed that the main findings are comparable (available upon request).

[2] To ascertain that our results are not affected (in that we drew erroneous conclusions) by our choice for a specific measurement of regional youth unemployment rates, we conducted sensitivity analyses using a different measurement. Specifically, we used information that Statistics Netherlands (2016) provides about 'the share of young people (ages 15–25) in the labor force without work but available for and seeking employment', which is also available for different regions. We reran our three-level logistic models with this alternative indicator and found that these findings (available upon request) do not differ substantially from our main models with our original indicator.

Table 2
Results of logistic 3-level analyses: logit effects, variance and ICC's of the null models (logit effects).
Source: VET survey (2011–2015) and VET expert survey (2011).

	Total sample			Employed sample								
	Paid job			Immediate entry			Horizontal match			Vertical match		
	b	(SE)	ICC	b	(SE)	ICC	b	(SE)	ICC	b	(SE)	ICC
Intercept	2.203***	(0.085)		1.361***	(0.071)		0.812***	(0.111)		0.963***	(0.083)	
Variance components												
Program level 3	0.590	(0.768)	0.152	0.423	(0.650)	0.115	1.251	(1.119)	0.276	0.648	(0.805)	0.164
Region level 2	0.092	(0.303)	0.027	0.009	(0.092)	0.003	0.067	(0.258)	0.020	0.027	(0.163)	0.008
N programs	114			114			114			114		
N regions	2,478			2,260			2,260			2,260		
N individuals	15,571			11,678			11,678			11,678		
Log-likelihood	−5,255.7			−5,673			−5,846.9			−5,797.3		

Significance levels: ***p < .001 (two-tailed tests).

standardized. Naturally, this measure is closely linked to attending either a work-based or school-based VET track (Pearson's r = .798, p = .000) in the Netherlands. The advantage of this measure compared to the work-based versus school-based track measure is that it also captures possible variation within these types of tracks, thus providing additional information beyond the dichotomy. Fig. 3 presents the pre-standardized distribution of this scale, which depicts even more variation (around 60 percent) between programs on this measurement.

We conducted interrater reliability tests for both vocational measures, which showed a strong agreement (with a reliability of ICC(2,2) = .730 and ICC(2,2) = .819 respectively) among pairs of professionals rating the same program within the same location.[3] Again, because of the highly standardized Dutch education system (e.g. Iannelli & Raffe, 2007; Van der Velden & Wolbers, 2007), we expect little variation between locations. The scores were thus aggregated to the level of educational programs and merged with the corresponding programs in the data from the VET survey. The two vocational measures are not strongly correlated (Pearson's r = .135, p = .152).

Returning to the VET survey, school-leavers had to indicate which of the following *VET levels* they had completed: 'basic vocational training, level 2', 'vocational training, level 3', and 'management training, level 4'. We incorporated these levels in the analyses by means of dichotomous variables, including an additional dummy for the missing values on this measurement. Next, *educational sector* was recoded into five dichotomous variables: economics, technology, agriculture, health care, and social work/welfare. All dummies were aggregated to the program level.

4.4. Individual control variables

Respondents were asked if they were male (0) or female (1). *Age* was measured in years and standardized. *Migration background* indicates whether at least one of the respondent's parents was born in a western or non-western foreign country, which is in accordance with Statistics Netherlands' definition (2018b). Three dummy variables were created based on this variable: 'native Dutch', 'western migration background', and 'non-western migration background'. The number of cases with missing values was small. Therefore, these cases were excluded from the samples (in both samples .6 percent). Respondents were asked what both *parents' educational level* was, of which the highest level was coded as the parental level of education. Based on the five response categories, three dummy variables were constructed: 'lower education' (primary and lower secondary education), 'intermediate education' (upper secondary general and vocational education), and 'higher education' (tertiary education). A separate dummy variable was included for cases that had missing information on one or both of the parents. *Year of graduation* was determined by means of register data (ROA). The data include graduation years 2010 to 2014, each of which was represented by a dummy variable.

Average graduation grade was measured by asking respondents what their total average graduation grade was, which ranged from '6.0' (minimum grade to pass exams) to '8.5 or higher'. Scores on this item were standardized. Cases with missing values were deleted in the total (1.4 percent) and employed (1.2 percent) sample.

Both *specific* and *generic skills* were measured using a self-reporting approach in which respondents were asked to indicate their own level of skills (on a 5-point Likert scale, ranging from mediocre [1] to excellent [5]). The average score of the items 'vocational knowledge' and 'the ability to apply vocational knowledge and techniques in practice' was calculated to construct a measure of specific skills (Cronbach's alpha = .643). Next, we constructed a measure for *generic skills* by averaging the scores on the following three items: written, oral, and numeracy skills (Cronbach's alpha = .607), which is in accordance with measures of previous research (e.g. Meng, 2006). These three components of generic skills are internationally measured this way, by means of widely used assessments such as the International Adult Literacy Survey (IALS) and the Programme for the International Assessment of Adult Competencies (PIAAC), both conducted by the OECD. Both skills measures were standardized, in which a higher score indicates a higher level of skill. Cases with missing values on specific and generic skills (10.2 and 9.1 percent, respectively) were deleted in the employed sample. Table 1 presents the descriptive statistics of all (pre-standardized) variables in the total and employed sample.

5. Analytical strategy

Since school-leavers are nested within regions (where the schools are located) and educational programs, and the labor market outcomes are all binary, the data were analyzed using logistic multilevel regression models. More specifically, the multilevel models included three levels: the individual level, the regional level (region of attended school), and the program level.

We chose for a hierarchical structure with educational programs as the highest level for two reasons. First and foremost, our main interest is whether the vocational impact differs between educational programs. This structure gives us the opportunity to assess systematic differences

[3] Within the VET expert survey, 48.9 percent of all educational programs (n = 133) is rated by only one respondent. To assess whether this endangers the reliability of the scores assigned by the raters, we used the programs (in the same location) that were rated by more than one rater to assess the extent to which coders' assessments of a program tend to overlap. These inter coder reliability tests showed a strong agreement between raters for those programs with more than one respondent. We are therefore confident that these are reliable measurements and the fact that some programs were rated by only one rater does not constitute a serious issue.

between programs. Next, given the high standardization in the Dutch education system (Iannelli & Raffe, 2007; Di Stasio & Van de Werfhorst, 2016), we argue that there is little variation within the same educational programs offered across different schools located in different regional areas. For example, a car mechanic program in region A is not that different from the car mechanic program in region B. The type of educational program attended is thus considered to be more important than the particular region or the attended school (Van der Velden & Wolbers, 2007).

6. Sensitivity analyses

To gauge the sensitivity of our results to the chosen hierarchical three-level model, we conducted three additional analyses. First, cross-classified models were conducted, in which regions and educational programs were not hierarchically nested but both were considered level 2 contexts. The main results from the cross-classified models (see Appendix A Tables A1 and A2) did not substantially differ from the results of our main analyses. Second, analyses were conducted in which the impact of *yearly* regional youth unemployment rates was examined (see Appendix A Tables A1 and A3). Lastly, we ran two-level models with programs as the highest level (see Appendix A Table A4). We did this because of the very low variance (highest = .092) and ICC (highest = .027) at the region level, which we discuss more elaborately in the next section. Overall, the findings from the sensitivity models did not differ substantially from our main models.

7. Results

7.1. Null models of logistic three-level analyses

To test the extent to which school-leavers' labor market outcomes are explained by differences between educational programs, regions and individuals, we start by estimating null models and corresponding intraclass correlations (ICC's) of the three-level logistic regression analyses presented in Table 2. As expected, school-leavers' labor market chances vary between programs. Of the observed variation in young people's chances of having a paid job, experiencing immediate entry, and horizontal and vertical job matching, 15.2, 11.5, 27.6, and 16.4 percent – respectively – is explained by differences between programs.

Next, we find very low intra-class correlations on the region level for every labor market outcome. This indicates that only 2.7, 0.3, 2.0, and 0.8 percent, respectively, of the variation in school-leavers' chances of having a paid job, experiencing immediate job entry, and a horizontal and vertical job match is explained by differences between regions. These findings thus indicate that youth's labor market chances are explained only to a very limited extent by regional differences, and vary more between educational programs than between regions. Nevertheless, we run the three-level models in order to examine the impact of the regional unemployment rates on youth's labor market chances.

7.2. Main results logistic multilevel models

Tables 3–5 report findings from our hierarchical logistic three-level models. All models control for gender, age, migration background, parental educational background, year of graduation, average graduation grade, specific and generic skills (only in employed sample), educational sector, and educational level (the findings of the controls are separately addressed in Appendix B). Main effects are shown in Table 3, while the statistical interaction terms of the vocational specificity measures with the regional unemployment rates are presented in Tables 4 and 5.

Based on the models presented in Table 3, we test whether the vocational specificity of educational programs has a positive impact on youth's labor market chances. We find a significant positive vocational impact in terms of the amount of *apprenticeship training* within programs on school-leavers' labor market chances, which is in line with our first hypothesis (H1a, H1b, H1c and H1d). Both network mechanisms (Rosenbaum et al., 1990) and signaling mechanisms (Spence, 1973) may drive these effects.

First, these positive effects can be explained by the stronger involvement of employers in the program and more apprenticeship training, which both increase the possibility of *contact* between students and employers (i.e. network mechanisms), increasing students' chances to enter a job more quickly after successful completion of the attended educational program and being allocated to a matching job (Iannelli & Raffe, 2007; Levels et al., 2014; Scherer, 2005). Apprenticeships can even lead to direct contact with possible future employers and their network. In our sample, around 35.6 percent of the school-leavers were previously an apprentice at their current job and 11.4 percent had previously been an employee at their current firm (total of 47 percent). Thus, apprenticeships seem to strongly promote school-leavers' labor market chances because they can often continue to work with the same employers who provided the training (Di Stasio & Van de Werfhorst, 2016).

Second, stronger involvement and more apprenticeship training both also increase the *signaling power* of educational qualifications (Breen, 2005; Iannelli & Raffe, 2007). A stronger involvement of employers in the curricular design of the programs ensures that the skills taught are not only attuned to their requirements (Levels et al., 2014), but also that they have more direct knowledge of the programs and the students they recruit (Iannelli & Raffe, 2007). As a result, clearer and more credible signals are sent to employers about school-leavers' (potential) productivity (Di Stasio & Van de Werfhorst, 2016; Raffe, 2008). Additionally, apprenticeship experiences can be easily quantified and put on resumes, signaling school-leavers' exact amount of on-the-job experience which provides easy-to-observe information about school-leavers' level of labor productivity (Protsch, 2017). Hence, both mechanisms may play a role in explaining why more vocationally specific programs increase young people's labor market chances, but we cannot empirically pinpoint the exact contributions of both mechanisms.

Next, in models in which we separately included both vocational measurements (Appendix C Table C1), the *vocational impact* in terms of amount of *vocational skills and knowledge* within programs has a significant positive effect on immediate entry, horizontal matching, and vertical matching (borderline). However, when the 'apprenticeship vocational measurement' is added to the models, only the effects on school-leavers' chances of immediate entry (borderline) and a horizontal job match remain significant (Table 3). Young people's likelihood of having a paid job eighteen months after graduation does not seem to be related to the specificity of educational programs measured in terms of vocational skills and knowledge. To facilitate the comparison of the estimates we also ran linear probability models (Appendix C Table C2). These findings are similar to our main three-level logistic models.

All in all, these findings seem to indicate that more vocationally specific programs improve youth's chances in the labor market and that this applies more strongly to the measure of vocational specificity focusing on the apprenticeship component of programs than to the measure focusing on the job-specific skills and knowledge component of programs. An explanation for this might be that even if a program is strongly oriented towards providing students with vocational knowledge and skills, this information may not be that clear of a signalfor employers, especially those who are not directly involved in the program (e.g. assessing and co-designing curricula). By contrast, the amount of apprenticeship training of programs can still be a clear and objective signal for employers, even if they are not involved in assessing or co-designing programs. Another possible explanation for this pattern of results is that the more positive impact of apprenticeship training is explained by the fact that *network* mechanisms are important drivers of the observed effects.

Table 3
Results of main effects logistic 3-level models of school-leavers' labor market chances (logit effects) (total sample = 15,571; employed sample = 11,678).
Source: VET survey (2011–2015) and VET expert survey (2011).

	Total Sample		**Employed sample**					
	Paid job		Immediate entry		Horizontal match		Vertical match	
	b	(SE)	b	(SE)	b	(SE)	b	(SE)
Program level								
Skill vocational specificity	0.027	(0.048)	0.083~	(0.049)	0.177*	(0.072)	0.086	(0.058)
Apprentice vocational specificity	0.302***	(0.054)	0.239***	(0.054)	0.378***	(0.076)	0.138*	(0.060)
VET level (level 2 = ref.)								
Level 3	0.925***	(0.163)	0.578***	(0.168)	0.774**	(0.244)	0.015	(0.196)
Level 4	1.130***	(0.151)	0.628***	(0.158)	0.939***	(0.233)	0.725***	(0.189)
Educational sector (economics = ref.)								
Agriculture	0.200	(0.312)	0.004	(0.326)	−0.330	(0.467)	−0.182	(0.381)
Technology	0.403**	(0.140)	0.028	(0.143)	0.376~	(0.208)	0.150	(0.170)
Health	0.778***	(0.158)	0.420*	(0.165)	0.769**	(0.256)	0.664**	(0.205)
Social work	−0.146	(0.197)	−0.599**	(0.212)	−0.370	(0.339)	−0.093	(0.266)
Region level								
Regional youth unemployment rate	−0.105***	(0.031)	−0.044~	(0.025)	−0.033	(0.027)	0.006	(0.024)
Individual level								
Female	0.000	(0.074)	−0.097	(0.071)	0.057	(0.067)	0.006	(0.067)
Age	−0.248***	(0.026)	−0.170***	(0.025)	−0.009	(0.025)	0.040	(0.025)
Migration background (Native Dutch = ref.)								
Western	−0.289*	(0.115)	−0.100	(0.114)	−0.067	(0.109)	−0.443***	(0.105)
Non-western	−0.927***	(0.073)	−0.573***	(0.085)	−0.346***	(0.087)	−0.306***	(0.088)
Parental educational background (low = ref.)								
Intermediate	0.067	(0.070)	0.048	(0.064)	0.089	(0.060)	0.185**	(0.059)
Higher	−0.085	(0.076)	−0.128~	(0.069)	0.079	(0.066)	0.155*	(0.066)
Missing	0.420***	(0.093)	−0.119	(0.104)	−0.056	(0.100)	0.140	(0.100)
Average graduation grade	0.064*	(0.026)	0.070**	(0.025)	0.104***	(0.024)	0.160***	(0.024)
Specific skills			0.208***	(0.026)	0.378***	(0.025)	0.213***	(0.025)
Generic skills			−0.053*	(0.027)	−0.194***	(0.026)	−0.107***	(0.026)
Graduation year (2010 = ref.)								
2011	−0.274~	(0.160)	0.079	(0.128)	−0.093	(0.119)	−0.172	(0.121)
2012	−0.513***	(0.122)	−0.227*	(0.093)	−0.398***	(0.089)	−0.445***	(0.091)
2013	−0.869***	(0.146)	−0.289*	(0.122)	−0.435***	(0.117)	−0.351**	(0.119)
2014	−0.588***	(0.123)	−0.104	(0.095)	−0.378***	(0.090)	−0.296**	(0.092)
Intercept	1.713***	(0.187)	1.175***	(0.177)	0.211	(0.237)	0.687***	(0.200)
N regions	2,478		2,260					
N programs	114		114					
Variance unemployment rate	0.004	(0.066)	0.001	(0.032)	0.005	(0.070)	0.001	(0.025)
Variance region level	0.015	(0.124)	0.004	(0.065)	0.000	(0.000)	0.035	(0.186)
Variance program level	0.190	(0.436)	0.235	(0.485)	0.673	(0.820)	0.407	(0.638)
Log likelihood	−5,017.5		−5,543.7		−5,981.9		−6,016.4	

Significance levels: ~p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests).

7.3. Results of the moderating role of regional youth unemployment rates

Our second hypothesis argues that the positive vocational impact of educational programs on youth's labor market opportunities is weaker when regional unemployment rates are higher. Starting with the main effects in Table 3, we find that higher regional unemployment rates are associated with lower chances of having a paid job and experiencing immediate entry (borderline significant), which is in line with findings from previous (country-national) studies (e.g. Scherer, 2005; Wolbers, 2007). Turning to the statistical interactions reported in Tables 4 and 5, we do not find a significantly weakening vocational impact on youth's labor market chances due to higher regional unemployment rates. Hence, no support for H2 is found.

We illustrate these interaction effects in Fig. 4, which shows the estimated coefficients of the vocational specificity measure (depicted on the y-axis) *conditional* on the values of the regional unemployment rate (x-axis). The overall pattern is that the impact of both vocational specificity measures changes very slightly or not at all as regional youth unemployment rates increase. Additionally, Fig. 5 depicts the average marginal effects of the vocational specificity of programs (x-axis) on the labor market outcomes (average predicted values on the y-axis) by regional youth unemployment rates. In order to provide clearer graphs, the regional youth unemployment rates are divided into low versus high regional youth unemployment rates (the lower and upper half of the distribution). Again, we see that both measures of the vocational impact do not differ substantially between low versus high regional unemployment rates. To conclude, all graphs support our prior conclusion that the vocational impact does not depend on or vary significantly with regional youth unemployment rates. Thus, our findings indicate that the otherwise positive vocational impact does *not* turn into a penalty when the regional youth unemployment rate is higher, at least not within the Dutch VET context.

Table 4
Results of interaction effects (skill) logistic 3-level models of school-leavers' labor market chances (logit effects) (total sample = 15,571; employed sample = 11,678).
Source: VET survey (2011–2015) and VET expert survey (2011).

	Total Sample		Employed Sample					
	Paid job		Immediate entry		Horizontal match		Vertical match	
	b	(SE)	b	(SE)	b	(SE)	b	(SE)
Program level								
Skill vocational specificity	0.032	(0.048)	0.086～	(0.049)	0.177*	(0.072)	0.086	(0.058)
Apprentice vocational specificity	0.302***	(0.054)	0.239***	(0.054)	0.378***	(0.076)	0.138*	(0.060)
Skill vocational*unemployment	0.029	(0.026)	−0.008	(0.023)	0.002	(0.025)	0.000	(0.022)
VET level (level 2 = ref.)								
Level 3	0.920***	(0.164)	0.577***	(0.168)	0.774**	(0.244)	0.015	(0.196)
Level 4	1.128***	(0.152)	0.630***	(0.158)	0.939***	(0.233)	0.725***	(0.189)
Educational sector (economics = ref.)								
Agriculture	0.200	(0.314)	0.004	(0.326)	−0.330	(0.467)	−0.182	(0.381)
Technology	0.401**	(0.140)	0.027	(0.143)	0.376～	(0.208)	0.150	(0.170)
Health	0.773***	(0.160)	0.419*	(0.165)	0.769**	(0.256)	0.664**	(0.205)
Social work	−0.143	(0.200)	−0.599**	(0.212)	−0.370	(0.339)	−0.093	(0.266)
Region level								
Regional youth unemployment rate	−0.101**	(0.031)	−0.044～	(0.025)	−0.033	(0.027)	0.006	(0.024)
Individual level								
Female	0.001	(0.074)	−0.097	(0.071)	0.057	(0.067)	0.006	(0.067)
Age	−0.248***	(0.026)	−0.170***	(0.025)	−0.009	(0.025)	0.040	(0.025)
Migration background (Native Dutch = ref.)								
Western	−0.289*	(0.115)	−0.101	(0.114)	−0.067	(0.109)	−0.443***	(0.105)
Non-western	−0.928***	(0.073)	−0.573***	(0.085)	−0.346***	(0.087)	−0.306***	(0.088)
Parental Educational Background (low = ref.)			0.048	(0.064)				
Intermediate	0.067	(0.070)	−0.128	(0.069)	0.089	(0.060)	0.185**	(0.059)
Higher	−0.085	(0.076)	−0.119～	(0.104)	0.079	(0.066)	0.155*	(0.066)
Missing	0.420***	(0.093)	0.048	(0.064)	−0.056	(0.100)	0.140	(0.100)
Average graduation grade	0.065*	(0.026)	0.070**	(0.025)	0.104***	(0.024)	0.160***	(0.024)
Specific skills			0.208***	(0.026)	0.378***	(0.025)	0.213***	(0.025)
Generic skills			−0.053*	(0.027)	−0.194***	(0.026)	−0.107***	(0.026)
Graduation Year (2010 = ref.)								
2011	−0.271～	(0.160)	0.078	(0.128)	−0.093	(0.119)	−0.172	(0.121)
2012	−0.511***	(0.122)	−0.228*	(0.093)	−0.398***	(0.089)	−0.445***	(0.091)
2013	−0.868***	(0.146)	−0.289*	(0.122)	−0.434***	(0.117)	−0.351**	(0.119)
2014	−0.587***	(0.123)	−0.104	(0.095)	−0.378***	(0.090)	−0.296**	(0.093)
Intercept	1.717***	(0.188)	1.176***	(0.177)	0.211	(0.237)	0.687***	(0.200)
N regions	2,478		2,260					
N programs	114		114					
Variance unemployment rate	0.004	(0.060)	0.001	(0.032)	0.005	(0.071)	0.001	(0.025)
Variance region level	0.016	(0.127)	0.004	(0.065)	0.000	(0.000)	0.035	(0.186)
Variance program level	0.191	(0.437)	0.235	(0.485)	0.673	(0.820)	0.407	(0.638)
Log likelihood	−5,016.9		−5,543.7		−5,981.9		−6,016.4	

Significance levels: ～p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests).

Table 5
Results of interaction effects (apprenticeship) logistic 3-level models of school-leavers' labor market chances (logit effects) (total sample = 15,571; employed sample = 11,678).
Source: VET survey (2011–2015) and VET expert survey (2011).

	Total Sample		Employed Sample					
	Paid job		Immediate entry		Horizontal match		Vertical match	
	b	(SE)	b	(SE)	b	(SE)	b	(SE)
Program level								
Skill vocational specificity	0.026	(0.048)	0.084～	(0.049)	0.176*	(0.072)	0.085	(0.058)
Apprentice vocational specificity	0.312***	(0.055)	0.241***	(0.054)	0.385***	(0.076)	0.141*	(0.061)
Apprentice vocational*unemployment	0.039	(0.031)	−0.019	(0.027)	0.036	(0.028)	0.011	(0.024)
VET level (level 2 = ref.)								
Level 3	0.925***	(0.163)	0.578***	(0.168)	0.775**	(0.244)	0.015	(0.196)
Level 4	1.128***	(0.151)	0.628***	(0.158)	0.937***	(0.233)	0.724***	(0.189)
Educational sector (economics = ref.)								
Agriculture	0.203	(0.313)	0.006	(0.327)	−0.332	(0.468)	−0.183	(0.381)
Technology	0.406**	(0.140)	0.026	(0.143)	0.380～	(0.209)	0.152	(0.170)
Health	0.784***	(0.159)	0.422*	(0.165)	0.771**	(0.256)	0.664**	(0.205)
Social work	−0.128	(0.199)	−0.592**	(0.213)	−0.370	(0.341)	−0.091	(0.267)
Region level								
Regional youth unemployment rate	−0.098**	(0.032)	−0.046～	(0.025)	−0.027	(0.028)	0.007	(0.024)

(*continued on next page*)

Table 5 (*continued*)

	Total Sample		Employed Sample					
	Paid job		Immediate entry		Horizontal match		Vertical match	
	b	(SE)	b	(SE)	b	(SE)	b	(SE)
Individual level								
Female	−0.001	(0.074)	−0.096	(0.071)	0.056	(0.068)	0.006	(0.067)
Age	−0.249***	(0.026)	−0.170***	(0.025)	−0.010	(0.025)	0.039	(0.025)
Migration background (Native Dutch = ref.)								
Western	−0.287*	(0.115)	−0.101	(0.114)	−0.066	(0.109)	−0.442***	(0.105)
Non-western	−0.927***	(0.073)	−0.572***	(0.085)	−0.348***	(0.087)	−0.306***	(0.088)
Parental educational background (low = ref.)								
Intermediate	0.065	(0.071)	0.049	(0.064)	0.087	(0.060)	0.184**	(0.059)
Higher	−0.087	(0.076)	−0.127~	(0.069)	0.077	(0.066)	0.154*	(0.066)
Missing	0.419***	(0.093)	−0.120	(0.104)	−0.056	(0.100)	0.140	(0.100)
Average graduation grade	0.065*	(0.026)	0.070**	(0.025)	0.105***	(0.024)	0.160***	(0.024)
Specific skills			0.208***	(0.026)	0.379***	(0.026)	0.214***	(0.025)
Generic skills			−0.053*	(0.027)	−0.194***	(0.026)	−0.107***	(0.026)
Graduation Year (2010 = ref.)								
2011	−0.270~	(0.160)	0.077	(0.128)	−0.089	(0.119)	−0.170	(0.121)
2012	−0.513***	(0.122)	−0.228*	(0.093)	−0.397***	(0.089)	−0.445***	(0.091)
2013	−0.869***	(0.146)	−0.288*	(0.122)	−0.435***	(0.117)	−0.351**	(0.119)
2014	−0.588***	(0.123)	−0.104	(0.095)	−0.378***	(0.090)	−0.296**	(0.092)
Intercept	1.715***	(0.188)	0.241***	(0.054)	0.213	(0.237)	0.688***	(0.200)
N regions	2,478		2,260					
N programs	114		114					
Variance unemployment rate	0.005	(0.067)	0.001	(0.030)	0.006	(0.079)	0.001	(0.024)
Variance region level	0.016	(0.127)	0.004	(0.063)	0.000	(0.000)	0.035	(0.187)
Variance program level	0.192	(0.438)	0.236	(0.486)	0.673	(0.821)	0.407	(0.638)
Log likelihood	−5,016.7		−5,543.5		−5,981.1		−6,016.3	

Significance levels: ~p < .10; *p < .05; **p < .01; *** p < .001 (two-tailed tests).

8. Conclusion and discussion

Previous research has repeatedly demonstrated that school-leavers from vocationally specific education systems experience a better integration into the labor market (e.g. Barbieri et al., 2016; Bol & Van de Werfhorst, 2011,2013; Levels et al., 2014). Yet, both empirically and theoretically notably less is known about the within-country heterogeneity in the vocational specificity of vocational education and training (VET) – i.e. about the variation between educational programs. Moreover, little is known about the impact of regional economic conditions on the relationship between the vocational specificity of educational programs and youth's labor market chances. This paper shed more light on these issues, focusing on the context of Dutch VET.

This paper, first of all, aimed to answer the question: *To what extent does the vocational specificity of educational programs in VET promote school-leavers' labor market integration?* Our findings showed that the specificity of educational programs in terms of amount of apprenticeship training improved school-leavers chances in terms of all labor market outcomes under investigation; it increased school-leavers' chances of having paid work, of immediate job entry after graduation, and of having a job that matches their (or a related) level and field of education (i.e. vertical and horizontal job matching). Apprenticeships may facilitate youth labor market integration because employers favor students who have a pre-existing relationship with the firm (Di Stasio & Van de Werfhorst, 2016). This applied to 47 percent of the school-leavers in our sample, indicating that workplace training operated as a 'foot in the door', which is in accordance with findings of a recent study by Protsch (2017). However, when measuring the vocational specificity of programs as the extent to which vocational knowledge and skills are provided in the program, we only found a positive impact on school-leavers' chances of immediate job entry and of having a job that matches their own (or related field) of education (i.e. horizontal job matching). We provide two possible explanations for these findings, which at the same time also explain why the apprenticeship measure overall had an more positive impact than the skill specificity measure.

It boils down to two ways in which more vocationally specific programs may improve youth's chances in the labor market: by means of (direct) contact with the labor market (i.e. network mechanisms) and clearer signals sent to employers (i.e. queuing mechanisms). Programs with more apprenticeship training obviously involve more apprenticeship training but also a stronger involvement of employers in the program. Both of these aspects may have increased i) *contact* between students and employers, and ii) the *signaling* power of qualifications, which may explain why students from these programs had better chances to have a paid job, enter a job more quickly and have a job that matches their educational qualifications (Breen, 2005; Iannelli & Raffe, 2007; Levels et al., 2014; Scherer, 2005).

Educational programs that were strongly oriented towards providing students with *vocational skills and knowledge* seemed to generally have a positive influence on school-leavers' chances of immediate entry and horizontal matching. This seems to indicate that, overall, the amount of apprenticeship training seems to be a stronger signal for employers to rely on than the vocational orientation of a program's curriculum (i.e. amount of vocational skills and knowledge), but it might also be an indication that network mechanisms are particularly important for increasing young people's labor market opportunities. Altogether, our findings indicate that strong signaling and network mechanisms can increase school-leavers' labor market opportunities in well-developed occupational labor market such as the Netherlands. These signaling or network processes seem to work especially through a program's amount of apprenticeship training. This might be of interest for future research aiming to further unravel which program features promote youth labor market integration and why, but also for policy-makers who aim to improve the school-work transition among recent graduates.

The second research question was: *To what extent do regional unemployment rates influence the positive impact of the vocational specificity of educational programs in VET on school-leavers' labor market integration?* We found that a higher regional youth unemployment rate decreases youth's chances of having a paid job and experiencing immediate job entry, which is in line with previous (country-comparative) research (De Lange et al., 2014; Scherer, 2005; Van der Velden & Wolbers, 2007;

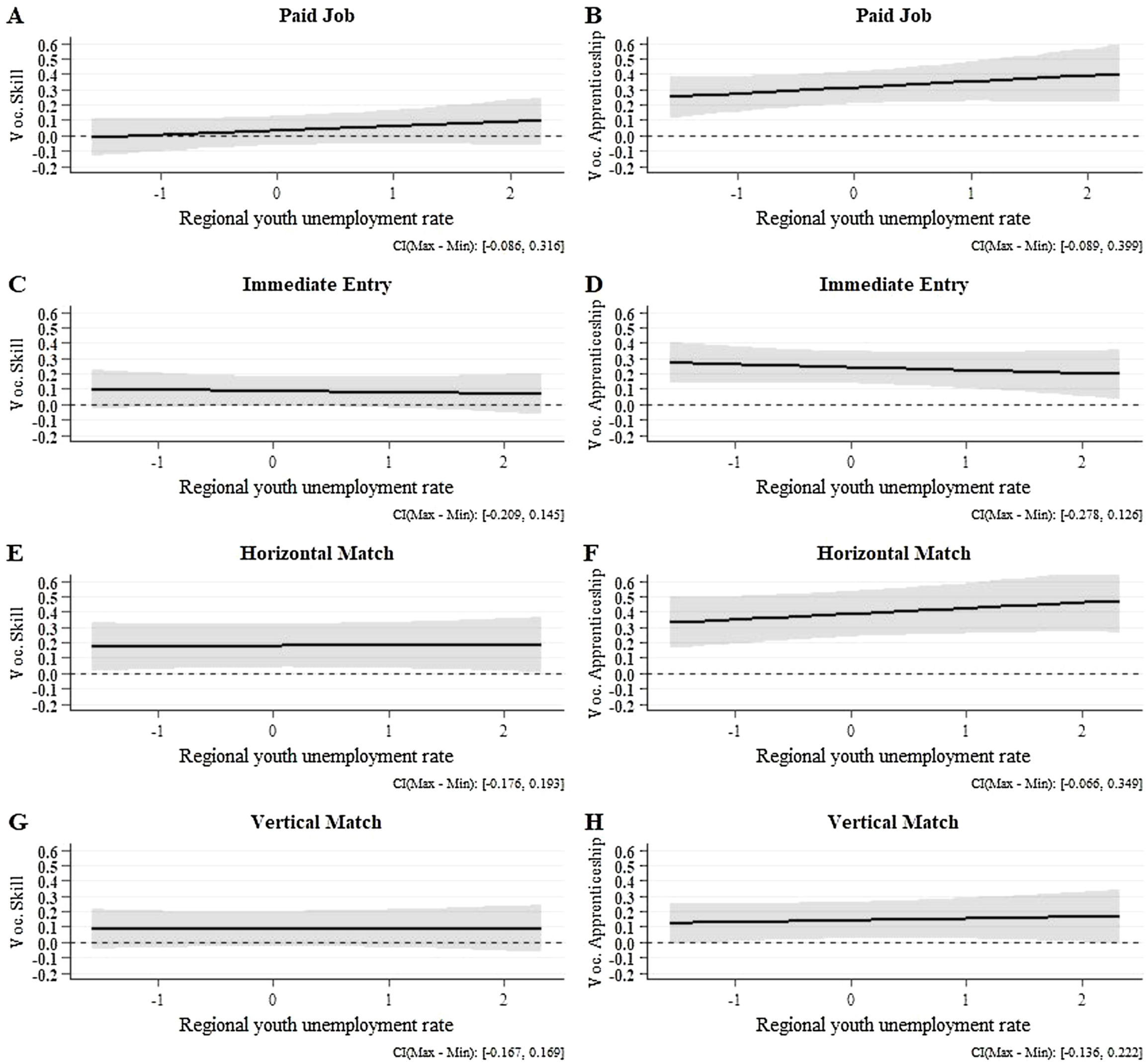

Fig. 4. Marginal effects of vocational measures (y-axis) on youth's labor market chances conditional on values of regional unemployment rate (x-axis).

Wolbers, 2007). However, importantly, the vocational impact does not turn into a penalty when regional youth unemployment rates are higher, at least not within the Dutch VET context. This finding thus seems to indicate that school-leavers from more specific educational programs are not less flexible or more limited in their labor market opportunities when regional economic conditions are unfavorable.

However, some caution is in order when interpreting this result. First, in our study, school-leavers' labor market chances are largely unrelated to differences in youth unemployment between regions in the Netherlands, perhaps because it is a relatively small country with fewer regional variations and considerably shorter commutes to other regions. Second, the regional youth unemployment rates were fairly stable over the five years we took into account, but it is possible that evidence of this relationship might have been found in this context in times of an economic recession. Hence, it is important to re-investigate whether the vocational impact varies with macro-economic conditions in future research. So far, studies theorizing and testing this moderating role are conspicuously absent, while the answer to this question may be particularly valuable for policymakers. This question thus needs to be re-examined in order to be able to give a well-rounded answer.

We would like to point out some limitations of this study, which may be addressed in future research. First, we cannot exactly pinpoint which of the two theoretical mechanisms that we discussed on our theory section – focusing on signals or networks respectively – underlie the vocational effects we observed, something that is a challenge in much of the research in this field (Bills, 2003; Di Stasio & Van de Werfhorst, 2016; Van de Werfhorst, 2011a). Future studies may seek to advance our insights in this respect, although it is also worth noting that these theories are not necessarily mutually exclusive and describe mechanisms that can operate simultaneously (Iannelli & Raffe, 2007, p. 50).

Second, a question that could not be addressed with the data used in this study, but that merits attention in the future is whether all school-leavers reap the benefits from graduating from a more vocationally specific program to the same extent. Recent research has drawn attention to the fact that in regards to certain outcomes (e.g. earnings) the benefits of vocational programs may be higher for school-leavers who actually end up in occupations that match their vocational educational qualifications (see Bol et al., 2019).

Finally, future research may strive to base the vocational specificity measures on information from larger numbers of VET professionals per educational program to further improve the reliability of these measures. However, compared to measures of programs' vocational specificity used in prior research (e.g. Coenen et al., 2015; Forster & Bol, 2018; Hanushek et al., 2017; Van der Velden & Wolbers, 2007), our measures were in unique in the sense that they were not interrelated to labor market outcomes but rather based on the educational programs itself, which is in closer alignment with the theoretical frameworks commonly tested in the school-to-work literature.

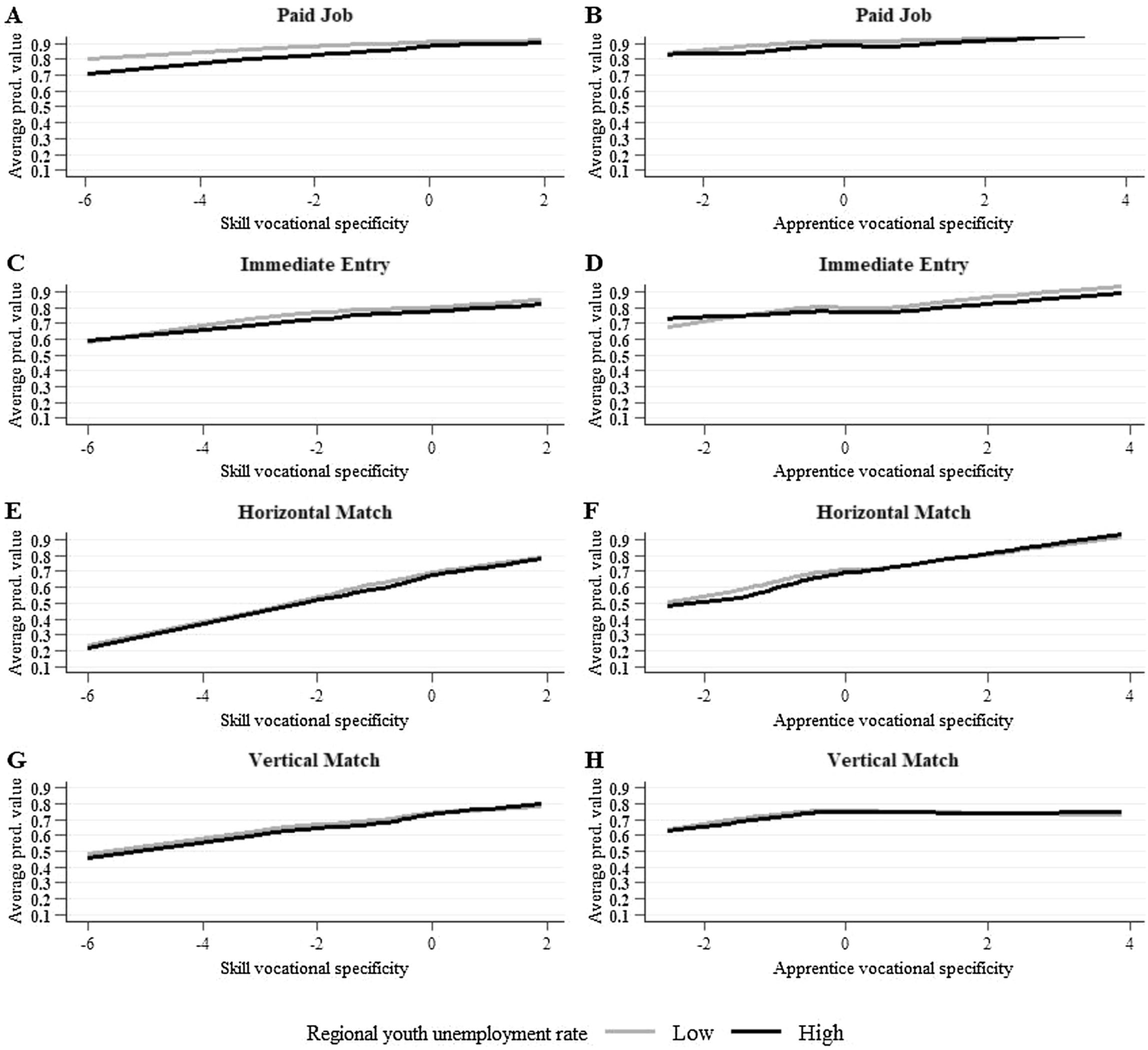

Fig. 5. Average predicted values on labor market outcomes based on (average marginal effects of) vocational measures with low and high regional youth unemployment.

Altogether, this paper moved beyond treating vocational education within a country as a homogeneous entity (Raffe, 2014, p. 182), and – in line with other research (Bol et al., 2019; DiPrete et al., 2017; Forster & Bol, 2018; Vogtenhuber, 2014) – found that there is indeed within-country heterogeneity in the vocational specificity of educational programs. We thereby provided more nuanced insights in differences in the vocational impact *between* programs in VET. Drawing on theoretical approaches focusing on queuing and networks mechanisms, we argued that possible differences in vocational specificity between VET programs may affect youth labor market integration. We were showed that more vocationally specific educational programs – especially those with a stronger emphasis on apprenticeship training – increase VET school-leavers' labor market opportunities in the Netherlands.

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Appendix A

Table A1
Robustness check main effects: cross-classified models with average and yearly regional unemployment rate (logit effects) (total sample = 15,571; employed sample = 11,678).
Source: VET survey (2011–2015) and VET expert survey (2011).

	Total Sample		**Employed Sample**					
	Paid job		Immediate entry		Horizontal match		Vertical match	
	Averaged b (SE)	Yearly b (SE)	Averaged b (SE)	Yearly b (SE)	Averaged b (SE)	Yearly b (SE)	Averaged b (SE)	Yearly b (SE)
Program level								
Skill vocational specificity	0.028	0.026	0.084 ∼	0.084 ∼	0.175*	0.174*	0.084	0.083
	(0.048)	(0.048)	(0.049)	(0.049)	(0.072)	(0.072)	(0.058)	(0.058)
Apprentice vocational specificity	0.297***	0.295***	0.238***	0.238***	0.376***	0.374***	0.136*	0.130*
	(0.054)	(0.054)	(0.054)	(0.054)	(0.076)	(0.076)	(0.060)	(0.060)
Region level								
Regional youth unemployment rate	−0.106**	−0.153***	−0.040	−0.049 ∼	−0.043	−0.064*	0.009	0.001
	(0.039)	(0.037	(0.027)	(0.026)	(0.032)	(0.030)	(0.023)	(0.024)
Intercept	1.694***	1.215***	1.174***	1.025***	0.204	−0.120	0.675***	0.354 ∼
	(0.189)	(0.151)	(0.177)	(0.159)	(0.237)	(0.224)	(0.199)	(0.182)
N regions / N regions-years	39	191	39	191				
N programs	114	114	114	114				
Variance unemployment rate	0.005	0.006	0.001	0.000	0.089	0.008	0.001	0.001
	(0.072)	(0.074)	(0.030)	(0.009)	(0.130)	(0.087)	(0.024)	(0.032)
Variance region level	0.018	0.044	0.003	0.008	0.008	0.009	0.000	0.000
	(0.134)	(0.209)	(0.057)	(0.092)	(0.087)	(0.097)	(0.000)	(0.014)
Variance program level	0.193	0.191	0.236	0.236	0.670	0.670	0.406	0.405
	(0.439)	(0.437)	(0.486)	(0.485)	(0.818)	(0.819)	(0.637)	(0.637)
Log likelihood	−5,015.1	−5,030.2	−5,543.4	−5,551.5	−5,980.5	−5,994.8	−6,018.4	−6,033.3

Significance levels: ∼p < .10; *p < .05; ** p < .01; *** p < .001 (two-tailed tests). *Note.* Only main findings are shown.

Table A2
Robustness check interactions: cross-classified models with average regional unemployment rate (logit effects) (total sample = 15,571; employed sample = 11,678).
Source: VET survey (2011–2015) and VET expert survey (2011).

	Total Sample		**Employed Sample**					
	Paid job		Immediate entry		Horizontal match		Vertical Match	
	M1 b (SE)	M2 b (SE)	M1 b (SE)	M2 b (SE)	M1 b (SE)	M2 b (SE)	M1 b (SE)	M2 b (SE)
Program level								
Skill vocational specificity	0.033	0.027	0.086 ∼	0.084 ∼	0.175*	0.174*	0.085	0.084
	(0.048)	(0.048)	(0.049)	(0.049)	(0.072)	(0.174)	(0.058)	(0.058)
Apprentice vocational specificity	0.297***	0.307***	0.238***	0.240***	0.376***	0.382***	0.136*	0.139*
	(0.054)	(0.055)	(0.054)	(0.054)	(0.076)	(0.076)	(0.060)	(0.060)
Skill vocational*unemployment	0.027		−0.008		0.000		0.002	
	(0.026)		(0.023)		(0.024)		(0.022)	
Apprentice vocational*unemployment		0.038		−0.019		0.035		0.012
		(0.031)		(0.027)		(0.028)		(0.023)
Region level								
Average Regional youth unemployment rate	−0.103**	−0.100*	−0.041	−0.043	−0.043	−0.037	0.010	0.010
	(0.039)	(0.039)	(0.027)	(0.027)	(0.032)	(0.033)	(0.024)	(0.024)
Intercept	1.697***	1.694***	1.175***	1.172***	0.204	0.206	0.675***	0.676***
	(0.190)	(0.190)	(0.177)	(0.178)	(0.237)	(0.237)	(0.199)	(0.199)
N regions	39	39						
N programs	114	114						
Variance unemployment rate	0.004	0.005	0.001	0.001	0.008	0.009	0.001	0.001
	(0.065)	(0.073)	(0.031)	(0.029)	(0.089)	(0.097)	(0.024)	(0.023)
Variance region level	0.018	0.018	0.003	0.003	0.008	0.008	0.000	0.000
	(0.135)	(0.134)	(0.057)	(0.057)	(0.087)	(0.087)	(0.000)	(0.000)
Variance program level	0.194	0.195	0.236	0.237	0.670	0.671	0.405	0.406
	(0.441)	(0.4421)	(0.486)	(0.487)	(0.818)	(0.819)	(0.637)	(0.637)
Log likelihood	−5,014.6	−5,014.4	−5,543.3	−5,543.1	−5,980.5	−5,979.7	−6,018.4	−6,018.3

Significance levels: ∼p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests). *Note.* Only main findings are shown.

Table A3
Robustness check **interactions**: cross-classified models with **yearly** regional unemployment rate (logit effects) (total sample = 15,571; employed sample = 11,678).
Source: VET survey (2011–2015) and VET expert survey (2011).

	Total Sample		**Employed Sample**					
	Paid job		Immediate entry		Horizontal match		Vertical match	
	M1 b (SE)	M2 b (SE)	M1 b (SE)	M2 b (SE)	M1 b (SE)	M2 b (SE)	M1 b (SE)	M2 b (SE)
Program level								
Skill vocational specificity	0.030	0.025	0.085 ~	0.084 ~	0.173*	0.172*	0.084	0.082
	(0.048)	(0.048)	(0.049)	(0.049)	(0.072)	(0.072)	(0.058)	(0.058)
Apprentice vocational specificity	0.294***	0.301***	0.238***	0.238***	0.374***	0.380***	0.130*	0.135*
	(0.054)	(0.055)	(0.054)	(0.054)	(0.076)	(0.076)	(0.060)	(0.060)
Skill vocational*unemployment	0.026		−0.010		−0.003		0.005	
	(0.026)		(0.023)		(0.024)		(0.022)	
Apprentice vocational*unemployment		0.028		−0.026		0.033		0.016
		(0.031)		(0.026)		(0.028)		(0.023)
Region level								
Yearly regional youth unemployment rate	−0.151***	−0.149***	−0.049 ~	−0.052*	−0.064*	−0.057 ~	0.001	0.002
	(0.037)	(0.037)	(0.026)	(0.026)	(0.030)	(0.030)	(0.024)	(0.024)
Intercept	1.217***	1.215***	1.025***	1.022***	−0.121	−0.118	0.354 ~	0.355 ~
	(0.151)	(0.151)	(0.159)	(0.159)	(0.224)	(0.224)	(0.182)	(0.182)
N region-years	191	191						
N programs	114	114						
Variance yearly regional unemployment rate	0.005	0.006	0.000	0.000	0.007	0.009	0.001	0.001
	(0.068)	(0.075)	(0.010)	(0.007)	(0.086)	(0.096)	(0.031)	(0.030)
Variance region level	0.044	0.044	0.008	0.008	0.009	0.009	0.000	0.000
	(0.209)	(0.209)	(0.092)	(0.092)	(0.097)	(0.096)	(0.012)	(0.014)
Variance program level	0.193	0.193	0.236	0.238	0.670	0.671	0.405	0.405
	(0.439)	(0.439)	(0.486)	(0.487)	(0.819)	(0.819)	(0.636)	(0.636)
Log likelihood	−5,029.7	−5,029.8	−5,551.4	−5,551.0	−5,994.8	−5,994.0	−6,033.3	−6,033.1

Significance levels: ~p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests). *Note.* Only main findings are shown.

Table A4
Results of main effects logistic 2-level models of school-leavers' labor market chances (logit effects) (total sample = 15,571; employed sample = 11,678).
Source: VET survey (2011–2015) and VET expert survey (2011).

	Total Sample		**Employed sample**					
	Paid job		Immediate entry		Horizontal match		Vertical match	
	b	(SE)	b	(SE)	b	(SE)	b	(SE)
Program level								
Skill vocational specificity	0.035	(0.048)	0.082 ~	(0.049)	0.176*	(0.072)	0.085	(0.058)
Apprentice vocational specificity	0.313***	(0.055)	0.244***	(0.054)	0.380***	(0.075)	0.138*	(0.060)
VET level (level 2 = ref.)								
Level 3	0.864***	(0.162)	0.606***	(0.168)	0.776**	(0.243)	0.021	(0.195)
Level 4	1.111***	(0.153)	0.637***	(0.159)	0.931***	(0.231)	0.715***	(0.188)
Educational sector (economics = ref.)								
Agriculture	0.136	(0.317)	0.035	(0.325)	−0.331	(0.466)	−0.219	(0.378)
Technology	0.380**	(0.141)	0.017	(0.144)	0.370 ~	(0.207)	0.147	(0.169)
Health	0.703***	(0.162)	0.426*	(0.167)	0.764**	(0.255)	0.655**	(0.204)
Social work	−0.205	(0.206)	−0.569**	(0.215)	−0.390	(0.335)	−0.111	(0.266)
Individual level								
Female	0.009	(0.073)	−0.101	(0.071)	0.056	(0.067)	0.009	(0.066)
Age	−0.249***	(0.026)	−0.173***	(0.025)	−0.011	(0.025)	0.040	(0.025)
Migration background (Native Dutch = ref.)								
Western	−0.310**	(0.114)	−0.106	(0.114)	−0.068	(0.109)	−0.433***	(0.104)
Non-western	−0.968***	(0.072)	−0.585***	(0.085)	−0.355***	(0.086)	−0.299***	(0.087)
Parental educational background (low = ref.)								
Intermediate	0.070	(0.070)	0.048	(0.064)	0.086	(0.060)	0.182**	(0.059)
Higher	−0.083	(0.076)	−0.129 ~	(0.069)	0.075	(0.066)	0.154*	(0.066)
Missing	0.412***	(0.093)	−0.121	(0.104)	−0.066	(0.099)	0.135	(0.099)
Average graduation grade	0.063*	(0.026)	0.071**	(0.025)	0.104***	(0.024)	0.158***	(0.024)
Specific skills			0.208***	(0.026)	0.376***	(0.025)	0.212***	(0.025)
Generic skills			−0.054*	(0.027)	−0.194***	(0.026)	−0.105***	(0.025)
Graduation year (2010 = ref.)								
2011	−0.290 ~	(0.159)	0.077	(0.128)	−0.101	(0.118)	−0.163	(0.120)
2012	−0.521***	(0.122)	−0.231*	(0.093)	−0.402***	(0.089)	−0.436***	(0.090)
2013	−0.871***	(0.145)	−0.288*	(0.122)	−0.437***	(0.117)	−0.337**	(0.118)
2014	−0.592***	(0.123)	−0.106	(0.095)	−0.382***	(0.090)	−0.287**	(0.092)
Intercept	1.760***	(0.186)	1.163***	(0.178)	0.220	(0.235)	0.681***	(0.199)
N regions	2,478		2,260					

(*continued on next page*)

Table A4 (*continued*)

	Total Sample		Employed sample					
	Paid job		Immediate entry		Horizontal match		Vertical match	
	b	(SE)	b	(SE)	b	(SE)	b	(SE)
N programs	114		114					
Variance program level	0.197	(0.444)	0.235	(0.485)	0.668	(0.818)	0.404	(0.635)
Log likelihood	−5,033.8		−5,545.7		−5,984.7		−6,018.9	

Significance levels: ~p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests).

Appendix B

Findings of Control Variables Main Models

Regarding our control variables from our main models in Table 3, we found that the older school-leavers are, the less likely they have a paid job or experience immediate entry after graduation. Next, school-leavers with a non-western migration background have lower labor market chances on all outcomes than their native Dutch counterparts, while school-leavers with a western migration background have lower labor market chances of having a paid and vertical matching job. School-leavers with middle or higher educated parents have higher chances of having a vertical matching job than school-leavers with lower educated parents. Interestingly, school-leavers with higher educated parents have lower chances (borderline significant) of immediate job entry after graduation compared to school-leavers with lower educated parents. A reason for this might be that they are in a lesser hurry (financially) to immediately enter the labor market.

Next, a higher graduation grade increases all school-leavers' labor market chances. A higher level of job-specific skills increases school-leavers' chances of immediate entry, and horizontal and vertical matching, whereas higher levels of generic skills decreases these chances. One's graduation year also seems to affect labor market chances. School-leavers graduated in the period from 2012 to 2014 have lower chances of a paid job, immediate entry (only to 2013), and horizontal and vertical matching compared school-leavers graduated in 2015.

Finally, we found interesting results regarding the impact of program characteristics. Compared to school-leavers from VET level 2, school-leavers from level 4 have higher chances of finding a vertical matching job. Moreover, school-leavers from both level 3 and 4 have higher chances of a paid job, immediate entry, and horizontal matching. Finally, school-leavers from the healthcare sector have better labor market chances on all outcomes than those from the economics sector. School-leavers from the technology sector also have better chances regarding finding a paid job than the economics graduates.

Appendix C

Table C1
Results of separate logistic 3-level models of vocational skill measurement on school-leavers' labor market chances (logit effects) (total sample = 15,571; employed sample = 11,678).
Source: VET survey (2011–2015) and VET expert survey (2011).

	Total Sample		Employed sample					
	Paid job		Immediate entry		Horizontal match		Vertical match	
	b	(SE)	b	(SE)	b	(SE)	b	(SE)
Program level								
Skill vocational specificity	0.079	(0.053)	0.130*	(0.052)	0.245**	(0.079)	0.111~	(0.058)
VET level (level 2 = ref.)								
Level 3	0.868***	(0.183)	0.538**	(0.180)	0.739**	(0.272)	−0.001	(0.200)
Level 4	0.838***	(0.162)	0.391*	(0.160)	0.575*	(0.246)	0.589**	(0.183)
Educational sector (economics = ref.)								
Agriculture	0.350	(0.353)	0.105	(0.351)	−0.180	(0.524)	−0.124	(0.390)
Technology	0.611***	(0.155)	0.190	(0.149)	0.653**	(0.226)	0.252	(0.168)
Health	0.832***	(0.184)	0.442*	(0.179)	0.790**	(0.288)	0.673**	(0.210)
Social work	0.125	(0.222)	−0.388~	(0.225)	−0.030	(0.374)	0.031	(0.267)
Region level								
Regional youth unemployment rate	−0.105***	(0.032)	−0.048~	(0.025)	−0.035	(0.027)	0.005	(0.024)
Individual level								
Female	−0.004*	(0.075)	−0.109	(0.072)	0.052	(0.068)	−0.001	(0.067)
Age	−0.237***	(0.026)	−0.162***	(0.025)	−0.002	(0.025)	0.043~	(0.025)
Migration background (Native Dutch = ref.)								
Western	−0.291*	(0.115)	−0.102	(0.114)	−0.067	(0.110)	−0.444***	(0.105)
Non-western	−0.938***	(0.073)	−0.582***	(0.085)	−0.357***	(0.088)	−0.312***	(0.088)
Parental educational background (low = ref.)								
Intermediate	0.068	(0.070)	0.051	(0.064)	0.092	(0.060)	0.186**	(0.059)
Higher	−0.090	(0.076)	−0.130~	(0.069)	0.077	(0.067)	0.154*	(0.066)
Missing	0.421***	(0.093)	−0.119	(0.104)	−0.053	(0.100)	0.140	(0.100)
Average graduation grade	0.064*	(0.026)	0.070**	(0.025)	0.104***	(0.024)	0.160***	(0.024)

(*continued on next page*)

Table C1 (*continued*)

	Total Sample		Employed sample					
	Paid job		Immediate entry		Horizontal match		Vertical match	
	b	(SE)	b	(SE)	b	(SE)	b	(SE)
Specific skills			0.211***	(0.026)	0.383***	(0.026)	0.215***	(0.025)
Generic skills			−0.055*	(0.027)	−0.196***	(0.026)	−0.107***	(0.026)
Graduation year (2010 = ref.)								
2011	−0.266~	(0.160)	0.082	(0.128)	−0.096	(0.120)	−0.169	(0.121)
2012	−0.505***	(0.122)	−0.223*	(0.094)	−0.398***	(0.090)	−0.444***	(0.091)
2013	−0.865***	(0.146)	−0.288*	(0.122)	−0.439***	(0.118)	−0.350**	(0.119)
2014	−0.583***	(0.123)	−0.102	(0.095)	−0.380***	(0.091)	−0.296**	(0.093)
Intercept	1.789***	(0.202)	1.245***	(0.186)	0.309	(0.260)	0.727***	(0.203)
N regions	2,478		2,260					
N programs	114		114					
Variance unemployment rate	0.005	(0.071)	0.001	(0.036)	0.004	(0.061)	0.001	(0.027)
Variance region level	0.013	(0.116)	0.005	(0.071)	0.066	(0.257)	0.034	(0.183)
Variance program level	0.290	(0.539)	0.295	(0.543)	0.873	(0.934)	0.434	(0.658)
Log likelihood	−5,031.7		−5,553.1		−5,990.3		−6,019.0	

Significance levels: ~p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests).

Table C2
Three-level linear probability models of school-leavers' labor market chances (logit effects) (total sample = 15,571; employed sample = 11,678). Source: VET survey (2011–2015) and VET expert survey (2011).

	Paid job		Immediate entry		Horizontal match		Vertical match	
	b	(SE)	b	(SE)	b	(SE)	b	(SE)
Program level								
Skill vocational specificity	0.001	(0.005)	0.014~	(0.008)	0.034**	(0.013)	0.018~	(0.010)
Apprentice vocational specificity	0.024***	(0.005)	0.034***	(0.008)	0.068***	(0.013)	0.027*	(0.010)
VET level (level 2 = ref.)								
Level 3	0.094***	(0.015)	0.091***	(0.026)	0.123**	(0.042)	0.001	(0.034)
Level 4	0.113***	(0.015)	0.102***	(0.025)	0.161***	(0.040)	0.128***	(0.033)
Educational sector (economics = ref.)								
Agriculture	0.033	(0.030)	0.009	(0.050)	−0.069	(0.083)	−0.036	(0.066)
Technology	0.036**	(0.013)	−0.003	(0.022)	0.063~	(0.036)	0.026	(0.029)
Health	0.061***	(0.014)	0.050*	(0.025)	0.092*	(0.044)	0.084*	(0.035)
Social work	0.001	(0.018)	−0.093**	(0.033)	−0.073	(0.058)	−0.013	(0.046)
Region level								
Regional youth unemployment rate	−0.013***	(0.003)	−0.006	(0.004)	−0.007	(0.005)	0.001	(0.004)
Individual level								
Women	−0.001	(0.007)	−0.016	(0.011)	0.010	(0.012)	0.002	(0.012)
Age	−0.027***	(0.003)	−0.027***	(0.004)	−0.001	(0.004)	0.007~	(0.004)
Migration Background (Native Dutch = ref.)								
Western	−0.028*	(0.012)	−0.017	(0.018)	−0.013	(0.019)	−0.082***	(0.019)
Non-western	−0.131***	(0.009)	−0.107***	(0.015)	−0.065***	(0.016)	−0.055***	(0.016)
Parental Educational Background (low = ref.)								
Intermediate	0.007	(0.007)	0.007	(0.010)	0.015	(0.010)	0.031**	(0.010)
Higher	−0.007	(0.007)	−0.019~	(0.011)	0.012	(0.011)	0.026*	(0.011)
Missing	0.041***	(0.009)	−0.019	(0.016)	−0.012	(0.017)	0.024	(0.017)
Average graduation grade	0.006*	(0.003)	0.011**	(0.004)	0.017***	(0.004)	0.027***	(0.004)
Specific skills			0.034***	(0.004)	0.068***	(0.004)	0.038***	(0.004)
Generic skills			−0.008*	(0.004)	−0.034***	(0.004)	−0.018***	(0.004)
Graduation year (2010 = ref.)								
2011	−0.019	(0.013)	0.011	(0.018)	−0.015	(0.019)	−0.026	(0.019)
2012	−0.039***	(0.010)	−0.033*	(0.014)	−0.065***	(0.015)	−0.071***	(0.015)
2013	−0.075***	(0.013)	−0.043*	(0.018)	−0.072***	(0.019)	−0.054**	(0.019)
2014	−0.047***	(0.010)	−0.015	(0.014)	−0.062***	(0.015)	−0.046**	(0.015)
Intercept	0.818***	(0.017)	0.748***	(0.027)	0.554***	(0.041)	0.647***	(0.034)
N region-programs	2,478		2,260					
N of programs	114		114					
Variance unemployment rate	0.000	(0.012)	0.000	(0.001)	0.000	(0.000)	0.000	(0.002)
Variance region-program level	0.001	(0.023)	0.000	(0.000)	0.000	(0.012)	0.000	(0.000)
Variance program level	0.002	(0.046)	0.005	(0.074)	0.020	(0.143)	0.012	(0.108)
Residual	0.092	(0.304)	0.151	(0.388)	0.168	(0.409)	0.169	(0.411)
Log likelihood	−3,676.5		−5,589.8		−6,304.6		−6,286.0	

Significance levels: ~p < .10; *p < .05; **p < .01; ***p < .001 (two-tailed tests).

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