European Sociological Review, 2019, Vol. 35, No. 5, 701–717
doi: 10.1093/esr/jcz031
Advance Access Publication Date: 24 June 2019
Original Article

Labour Market Effects of General and Vocational Education over the Life-Cycle and across Time: Accounting for Age, Period, and Cohort Effects

Jesper J. Rözer* and Thijs Bol

Department of Sociology, Amsterdam University, 1018 WV Amsterdam, The Netherlands

*Corresponding author. Email: j.j.rozer@uva.nl

Submitted September 2017; revised April 2019; accepted April 2019

Abstract

A recent literature argues that the labour market returns to vocational education vary over the life cycle. Graduates with an occupation-specific educational degree have a smooth transition into the labour market but experience difficulties later in their career when their specific skills become obsolete. This life course penalty to vocational education is expected to be particularly strong in periods of rapid technological change. Existing literature has mostly studied this topic from the perspective of age effects but focused less on cohort and period effects. Moreover, it is unclear to what extent lower returns to vocational education in the late career vary across time periods. Using Labour Force Survey data for the Netherlands (1996–2012) we find that having a more occupation-specific educational degree increases the likelihood of being employed in early life and lowers the average job status. This initial advantage of a higher employment probability declines with age, and the disadvantage in job status increases as workers grow older. We find that these life-cycle effects have not, or only marginally, changed over time.

Introduction

Recent studies claim that labour market returns to vocational education vary over the life cycle (Krueger and Kumar, 2004; Cörvers *et al.*, 2011; Forster, Bol and Van de Werfhorst, 2016; Woessman, 2016; Brunello and Rocco, 2017; Golsteyn and Stenberg, 2017; Hampf and Woessman, 2017; Hanushek *et al.*, 2017; Forster and Bol, 2018). The main argument is that at the start of the career a vocational degree enhances the transition from school to work by providing ready-to-use skills and relevant work experience. However, occupational task demands change and the occupation-specific skills that were acquired in education become obsolete later in the career. Workers with a general educational degree, in contrast, have more general skills and are therefore much more able to adapt to changing task demands in the labour market. As a result, vocational graduates are argued to suffer a 'penalty' in the later career, having a lower employment probability and less desirable jobs than workers with a general degree.

In studying the trade-off between early career advantage and late career disadvantage of occupation-specific skills previous studies have taken an age approach, which is based on the idea that labour market returns to occupation-specific education vary over an individual's life course (e.g. Golsteyn and Stenberg, 2017; Hanushek *et al.*, 2017; Forster and Bol, 2018). Less attention has been paid to the influence of period and cohort effects.

This can be problematic because the importance of the age effect might be biased when it is not separated from period and/or cohort effects. Maybe workers with a vocational degree do not experience a penalty later in their career because they age, but because the labour market returns to a vocational degree vary across periods or were lower for older cohorts.

Longitudinal studies have tried to separate age effects from period and cohort effects by controlling either for period or cohort effects, next to including age (e.g. Brunello and Rocco, 2017; Golsteyn and Stenberg, 2017). At the same time it remains unknown to what extent, and in what direction, results are biased when either period or cohort effects are not taken into account. Understanding the role of period and cohort effects is vital for studies that cannot sufficiently control for either one of the two, for example because studies use a cross-sectional design (e.g. Hanushek *et al.*, 2017) or because they only cover a short period (e.g. Forster and Bol, 2018).

In this article, we investigate how cohort and period contribute to the lifecycle effects of occupation-specific education. To investigate the role of period and cohort is not just a methodological contribution: the theoretical underpinnings of the life-cycle hypothesis are not solely based on an age effect, but on an interaction between age and period effects as well. A clear expectation in the literature is that the effects of vocational education will decrease over the life cycle, but especially in a context of rapid technological innovation, when in education acquired specific skills much more quickly become outdated and obsolete (Green, Wolf and Laney, 1999; Green, 2002; Woessman, 2016; Forster, Bol and Van de Werfhorst, 2016). While the hypothesis on the role of technological change is made explicit in many studies, it has so far not been tested.

Our main research question is: *what are the consequences of a general versus more vocational specific educational degree for the likelihood of being employed and job status across the life cycle, and do these consequences differ over time?* In contrast to previous studies we use job status rather than income as a proxy for the desirability of a job. Job status not only captures the income attached to a job, but also the skills that are needed for the job, as well as how desirable (other) people think the job is. We investigate this question by analyzing data from the Dutch Labour Force Survey (*Enquete Beroepsbevolking*, EBB) for the years 1996 to 2012. The repeated cross-sectional data allow for disentangling age, period, and cohort effects as good as possible. Although having a repeated cross-sectional design we cannot follow the same respondents over time, nor rule out that some respondents self-select into a certain type of education on factors that we do not observe (motivation, skills, socio-economic background). These two factors make it impossible to make strong causal claims.

Following recent studies, we measure the 'vocationality' of educational programs by looking at linkage strength to the labour market. The more graduates of an educational program work in the same small set of occupations, the stronger the linkage (DiPrete *et al.*, 2017; Bol *et al.*, 2019). The main advantage of this method is that a more gradual distinction can be made between the extent to which educational programs provide students with (occupation-)specific skills. A binary distinction between vocational and general education obscures a lot of relevant variation within these categories in the extent to which students obtain specific skills. For example, although both being (general) university studies, medical students often acquire very specific vocational skills and end up working in just a few occupations. Sociology students, in contrast, acquire much more general skills and eventually scatter out over a wide variety of different occupations.

A more fine-grained measure of vocational specificity closely relates to policy debates about what skills need to be taught in educational programs. Should educational programs broaden their scope and prepare students for a large set of occupations, for example by paying more attention to general skills like mathematics, reading, and civic attitudes? Or should educational programs instead narrow their focus and emphasize specific occupational skills in their curriculum? Our study can inform these debates by showing the short and long-term labour market outcomes of educational programs with a weak and strong linkage.

Vocational Education and Labour Market Outcomes over the Life-Cycle and across Time

School to Work Transitions

Vocational education is generally regarded to smoothen the transition to the labour market. Studies for example find that individuals with a more vocationally specific degree find a job more quickly (Shavit and Müller, 1998; Breen, 2005; Biavaschi *et al.*, 2012; Noelke, Gebel and Kogan, 2012). There are several mechanisms that explain this relation.

First, in vocational education, students obtain specific skills that directly translate to tasks that are demanded in occupations for which they are educated. As a consequence, vocational graduates are immediately productive and requires less on-the-job training than

graduates with a general degree, making them more attractive for employers (Ryan, 2003; Scherer, 2005; Leuze, 2007; Van de Werfhorst, 2011; Noelke, Gebel and Kogan, 2012). Second, irrespective of whether vocational graduates are really more productive, vocational degrees *signal* high productivity because employers expect that students were taught marketable skills and attitudes (Arum and Shavit, 1995). Third, graduates from vocationally specific educational programs often enter the labour market with useful social networks, for example because they took an apprenticeships. This makes networks a more valuable resource for vocational graduates than general graduates in finding employment (Rosenbaum *et al.*, 1990). In this study we do not aim to differentiate between these mechanisms, but it is clear that many different theories come to the same conclusion: compared to students with a general degree, vocational graduates will experience a smoother transition from school to work.

Several studies show that a vocational degree is also associated with a comparatively prestigious job at the start of one's career (e.g. Wolbers, 2007; Roksa and Levey, 2010; Brunello and Rocco, 2017). One explanation for this is that a vocational degree leads to more job experience than a general degree, resulting in a more attractive first job (Silverberg *et al.*, 2004; Biavaschi, 2012). However, the literature is mixed, and other studies find that vocational graduates work in less prestigious jobs than workers with a general degree (e.g. Shavit and Müller, 1998; Iannelli and Raffe, 2007). Here the argument is that specific skills only relate to a small section of jobs, which makes workers inflexible and unable to move to more desirable (and more prestigious) jobs (Ryan, 2001). Furthermore, vocational programs typically train their students for manual or craft jobs that have a relatively low status, whereas general tracks more often train students for management or professional functions that are often considered to have a higher prestige (Iannelli and Raffe, 2007; Wolbers, 2007; Roksa and Levey, 2010). Previous studies have opposing findings, which may partly be explained by their different definition of what constitutes a vocational degree.[1] While the literature is almost unanimous about the positive effect of vocational education on finding employment, it remains unclear whether a vocational degree also leads to a more desirable occupation at the start of one's career.

Vocational Education and the Life-Cycle

Recent studies suggest that individuals with a general degree have better labour market prospects over their full life-cycle than individuals with a vocational degree (e.g. Stenberg and Westerlund, 2015; Brunello and Rocco, 2017; Golsteyn and Stenberg, 2017; Hanushek *et al.*, 2017; Forster and Bol, 2018; Middeldorp, Edzes and Van Dijk, 2019). Different mechanisms are used to explain the long-term advantages of a general degree.

First, vocational and general educational programs prepare students for different kinds of jobs. Vocational educational programs and apprenticeships tend to be confined to manual and crafts jobs where technological innovation and company growth are limited, leading to less potential growth in opportunities for vocational graduates (Biavaschi *et al.*, 2012).

Second, students with a general degree have to take more on-the-job training before becoming productive. On average they will require a substantial amount of training before they are ready for the job they are hired for. In contrast, students with a vocational degree need much less training, but this also means that over their career they participate less in lifelong learning to keep their skills updated (Brunello, 2001; Vogtenhuber, 2015). More on-the-job training makes workers more flexible when facing technological and/or organizational changes, leading to more prosperous employment opportunities for general graduates later in their career (Brunello, 2001; Krueger and Kumar, 2004).

A third argument is that the specific skills of workers with a vocational degree depreciate faster than the abstract skills of workers with a general educational degree. Workers with a general degree have more abstract skills that will remain more valuable later in the career (Brunello and Rocco, 2017). While occupation-specific skills can only be used in a limited number of jobs, general skills are transferable to a wide variety of jobs, meaning that workers with a vocational degree will be relatively more vulnerable to changes in the labour market (Weber, 2014).

Fourth, and related to the previous arguments, general skills—like numeracy, literacy, and communications skills—are argued to improve the learning and acquiring of *new* skills. The argument is that individuals with more general skills will adapt to new situations more easily. Learning begets learning, and being trained in general skills early on makes it easier to develop (or sustain) these skills later in life (Cunha and Heckman, 2007). Again, this would lead to the expectation that graduates from a general educational program reap benefits later on as they are better able to obtain new skills.

For the aforementioned reasons, we expect that in the long-run workers with a general degree experience a labour market advantage over graduates from vocational education. Our first hypothesis concerns the employability

of general and vocational graduates. We expect that vocational graduates are more likely than general graduates to be employed at the start of their career, but this pattern reverses later in their career, as generally schooled workers will be more flexible. The second hypothesis concerns the status of the job that general and vocational graduates work in. While vocational education may effectively protect against unemployment by smoothening the transition to the labour market and giving access to long-term contracts, it also reduces the incentive or possibility to search for higher status jobs (Korber and Oesch, 2016). For this reason, we expect that individuals with a general degree will see a steeper rise in their job status over their career compared to vocational graduates.

Change across Time

While the previous section has dealt with the difference between vocational and general education purely from an age perspective (early or late in the career), the declining returns to vocational education over the life cycle may be especially strong in recent periods. At least three—interrelated and not mutually exclusive—reasons motivate this claim.

First, occupational skill demands changed rapidly due to an increasing rate of technological change (Acemoglu and Autor, 2011; Brynjolfsson and McAfee, 2014; Frey and Osborne, 2017; Nedelkoska and Quintini, 2018). This is exemplified by the exponential growth of computing power (Supplementary Appendix A, Panel 1 A), and the computing power that is needed for the same calculations (Supplementary Appendix A, Panel 1B). Technological developments have had large consequences for the labour market in which many occupational tasks and occupations have (dis)appeared or changed. For example, decisions made by bank employees are increasingly guided by computers, similar to the work of surgeons, who are more and more assisted by machines that take over parts their work (Autor, 2010). With rapid technological change, the types of skills that are required have changed rapidly as well. Where being able to calculate quickly used to be an important task for a banker, now one of the main requirements is that one is able to work with the software that does these calculations. As we have argued above, general education is argued to provide students with more flexible skills than vocational education. Therefore, in periods of rapid technological change, we expect that the late-career advantage of general education (or late-career disadvantage of vocational education) is stronger (Krueger and Kumar, 2004; Woessman, 2016; Hanushek *et al.*, 2017).

Second, due to technological change and the offshoring of (primarily) jobs for vocational graduates to developing countries, the labour market value of vocationally specific skills will decrease (Acemoglu and Autor, 2011; Liu and Grusky, 2013). In the Netherlands, the country under study, between 1996 and 2012 typical occupations for vocational graduates such as clerks, craftsmen, and machine operators have declined with 7 per cent (Supplementary Appendix A, Panel 2 A). General education, in contrast, prepares students more often for different types of jobs, including service sector jobs that are increasingly in demand. There seems to be a tendency that occupation-specific skills become less important in the workplace, while general skills, like communication and computer skills, become more important (Autor and Dorn 2009; Supplementary Appendix A, Panel 2B). These over-time developments again favour workers with a more general educational degree.

Third, labour markets have become increasingly flexible, for example by a decline of union membership and liberal policies such as the easing of dismissal rules (Autor, 2010; Cutuli and Guetto, 2012). A consequence is that employees increasingly have temporary contracts. Compared to other countries, this rise in temporary work has been particularly large in the Netherlands (Supplementary Appendix A, Panel 3 A, see also Supplementary Appendix 3B). Temporary employees more often switch between jobs than employees with a permanent contract: in the Netherlands the percentage of employees that switched a job within a year increased by 38 per cent from 2004 to 2018. For each new (type of) job employees need different skills. Again the argument here would be that increase in job-switching would harm students with a vocational training more than students from general education, because this second group typically has a broader set of skills (Weber, 2014; Brunello and Rocco, 2017; Hanushek *et al.*, 2017). In other words, graduates from a more general educational program will be better prepared for the increasingly flexible labour market.

These three arguments indicate that there are reasons to suspect that the life cycle effect (or age effect) might instead be a period effect. Existing studies acknowledge that these two factors can be intertwined: Hanushek *et al.* (2017) clearly state that the decline in labour market returns to vocational education is partly explained by rapid technological change. Furthermore, the three arguments show that period and life cycle effects may work in tandem with each other: In more recent periods rapid technological change and flexibilization of the labour market may have increased the negative effects

associated with having a vocational degree (especially in the late-career).

Data

The Dutch Labour Force Survey

We use the Dutch Labour Force Survey (*Enquete Beroepsbevolking*, EBB) to test our hypotheses. The EBB is a household survey in which up to 15 household members can participate. Until 1999, the EBB was a cross-sectional survey for which in every month a random sample of respondents were interviewed. In 1999 a rotating panel design was introduced. From then on, each respondent in the sample is approached for five consecutive interviews over a period of twelve months. To not further complicate our analyses, we only select respondents at their first interview. Only respondents out of education and between the age of 20 and 65 are included in our sample (cf., Forster, Bol and Van de Werfhorst, 2016). After listwise deletion of missing values we obtain an analytic sample of 1,143,652 respondents.

Employment and Job Status

We analyze two dependent variables. First, in line with previous studies (e.g. Forster, Bol and Van de Werfhorst, 2016; Hanushek *et al.*, 2017) we study employment, distinguishing respondents who are not employed (coded as 0) from those who are (coded as 1). Not employed includes respondents who are unemployed and looking for a job, but also people that have left the labour market for reasons like retirement and inability to work. This approach is in line with the bulk of the literature on life cycle effects of vocational education (Forster, Bol and Van de Werfhorst, 2016; Hanushek *et al.*, 2017).

The second dependent variable is job status. Job status not only captures the income attached to a job, but also the skills that are required for the job. Job status reflects one of the most important dimension in social interaction, and captures—compared to income—a broader and more social aspect of job desirability. The respondent's job title was measured using the ISCO-08 classification scale. These scores were rescaled to the International Socio-Economic Index '08 (ISEI) of occupational status (Ganzeboom and Treiman, 2010). ISEI ranges from 10 for occupations with the lowest status to 90 for occupations with the highest status.

The Vocational Specificity of Educational Programs: Linkage Strength

The vocational specificity of educational programs is operationalized by measuring the linkage strength between an educational degree and the labour market. The more students are clustered in a (set of) occupation(s), the higher the linkage strength. The intuition here is that when there is a strong emphasis on specific occupational skills in education, graduates with a similar degree will cluster in the same occupations (cf. Forster and Bol, 2018). This occupational clustering of graduates from the same educational program (defined by both field and level) then provides a measure of vocational specificity that is gradual, in contrast to the dichotomous distinction between general and vocational that the majority of the literature relies on. In defining vocationality of educational programs by looking at the linkage strength we follow recent work (DiPrete *et al.*, 2017; Forster and Bol, 2018; Bol *et al.*, 2019), but deviate slightly from older studies that use 'linkage' to describe the involvement of employers in vocational education. Shavit and Müller (2000), for example, use linkage to describe if employers engage in apprenticeship-training at the workplace or the curricular design in vocational schools. Both definitions are, however, connected: a stronger involvement of employers in vocational education most likely results in a stronger link between educational programs and occupations.

Technically, we use a measure of local segregation to express linkage strength. The local segregation (M_g) for each educational program can be formally defined as:

$$M_g = \sum_j P_{j|g} \mathrm{Log}\left(\frac{P_{j|g}}{P_j}\right) \quad (1)$$

Where $p_{j|g}$ is the probability of being in an occupation j conditional on that one has the educational degree g. Local segregation shows the extent to which workers from a similar educational category (g) are spread across occupations, compared to all workers.

Measuring the local linkage requires information on educational programs and occupations. Educational programs are measured using the Dutch educational classification (*Standaard onderwijsindeling*, SOI). In this classification each educational program is identified by a six-digit code in which the first two digits represent the level of education (as an ISCED scale) and the four remaining digits the field of study, for example social sciences or management. To avoid that our measure is based on small cells, we follow DiPrete *et al.* (2017) and only use the first two digits of the field code. When fewer than 100 respondents followed this educational program, they were left out of the analyses. This leaves us with 312 level-field combinations.

Occupations are measured using the International Standard Classification of Occupations (ISCO 2008). To obtain detailed information but still maintain enough

cases per occupation, we again follow DiPrete *et al.* (2017) and only use the first three digits of each ISCO-08 code. Occupations within the military (major ISCO group 0) are excluded from all analyses. This selection results in 128 occupational categories that are used in calculating the linkage strength of educational programs.

Table 2 describes the linkage strength for the 10 educational programs with the highest and lowest linkage score. Upper and lower secondary educational programs have the weakest linkage, in particular when they are not related to a specific field. For example, individuals who dropped out from the higher levels of 'high school' (lower secondary education high level, e.g. *havo/vwo* year 1/3), start to work in very different occupations. By contrast, individuals with a higher educational degree within a specific field are more likely to start to work and stay in that field. Individuals with a doctoral degree in health (higher education third phase) have the highest linkage strength and almost all become medical doctors.

Control Variables

We add several control variables. Employment probabilities differ considerably between educational levels, and since we are interested in an effect of vocational specificity and not an effect of educational level, we include a series of dummy variables for educational level in our model. Educational level is measured by the first two digits of the SOI classification, which is comparable to the ISCED 2011 classification. This means that our models predict the within-level effects of vocational specificity on employment and job status. Second, we control for the nationality of the respondents, coded as (1) being Dutch when a respondent had the Dutch nationality or was born in The Netherlands, and (0) otherwise. Besides these control variables, we include age and period, as we will discuss below in length. Descriptive statistics of this and other variables are presented in Table 1.

Method

Our main empirical challenge is to disentangle age, period, and cohort (APC) effects as they are perfectly colinear: Period = Age + Cohort. Unfortunately, there is no perfect solution to this exact collinearity, because the collinearity is present in the population as a whole, instead of just in the sample (Bell and Jones, 2015).

Nevertheless, if we are prepared to make certain assumptions about APC effects, inference is possible. The crucial assumption to make here is that there is a zero age, period, or cohort effect, which correspondingly

Table 1. Descriptive statistics

			Men			Women		
	Min	Max	Perc.	Mean	SD	Perc.	Mean	SD
Having a job			82.8			64.6		
Job status	3	89		45.8	10		41.4	15.1
Linkage (*std.*)	−1.3	15.1		0.2	1		−0.2	1
Age	20	65		43	12.1		43	12
Period	1996	2012		2003	4.9		2003	4.9
Education								
Pre primary			1.3			1.5		
Primary			7.3			8.8		
Lower secondary, low			1.6			2.3		
Lower secondary, intermediate			0.3			0.4		
Lower secondary, high			19.5			23		
Upper secondary, low			6.2			4.8		
Upper secondary, intermediate			15.4			17.1		
Upper secondary, high			20.7			19.2		
Higher education, first phase, low			1.1			0.7		
Higher education, first phase, intermediate			15.9			15.3		
Higher education, first phase, high			0.3			0.3		
Higher education, second phase			8.6			5.9		
Higher education, third phase			1.7			0.8		
Ethnicity (native)			97			96.7		

$n = 566{,}094$ (men), $n = 577{,}558$ (women).

Table 2. Linkage strength of the top, and bottom 10 educational programs according to their linkage scores

Rank	SOI	Level	Field	Link
1	4299	Upper secondary, intermediate level	Unknown	−1.323
2	4201	Upper secondary, intermediate level	General	−1.282
3	3301	Upper secondary, high level	General	−1.249
4	4301	Upper secondary, high level	General	−1.162
5	4133	Upper secondary, low level	Management	−1.087
6	5299	Higher education, first phase, intermediate	Unknown	−1.072
7	3335	Lower secondary, high level	Administration	−0.983
8	4323	Lower secondary, high level	Social sciences	−0.972
9	3332	Lower secondary, high level	Commercial	−0.946
10	4233	Upper secondary, middle level	Management	−0.914
–				
302	6067	Higher, second phase	Technicians, with differentiation	2.955
303	7020	Higher, third phase	Humanities, social sciences and arts	3.011
304	5140	Higher, first phase	Mathematics, natural sciences and computer science	3.027
305	5192	Higher, third phase	Hospitality, tourism and leisure	3.051
306	7087	Higher, third phase	Health	3.220
307	7022	Higher, third phase	Humanities, other	3.302
308	7035	Higher, third phase	Administration	3.481
309	7042	Higher, third phase	Public order, safety	3.620
310	4342	Upper secondary, high level	Public order, safety	3.649
311	7041	Higher, third phase	Administration	4.749
312	7081	Higher, third phase	Health	5.079

does not have to be estimated and hence can be left out of the equation (Bell and Jones, 2015). This assumption is necessary, because only two of the three APC effects can be estimated simultaneously. To be clear, this remains a strong assumption: when one term (age, period, or cohort) is excluded but its effect is *not* zero, the other terms will (wrongfully) partially capture this effect.

In this study, we assume that there is a zero cohort effect. This assumption might be violated when there are some cohorts that have a higher chance to be employed at certain points in their life than others. For example, unemployment was remarkably high in The Netherlands in the late 1980s, and the cohort that entered the labour market then may have remained more likely to be unemployed during their career. Studies have documented scarring effects of unemployment (Gregg and Tominey, 2005; Gangl, 2006; Nilsen and Reiso, 2014), so growing up at the wrong point in time might have lasting effects. However, Wolbers (2016) shows that the effect of having a higher chance of being unemployed in the 1980s disappeared in the long run after people got their first job in the Netherlands, possibly due to the economic boom in the 1990s. While the Dutch results show less evidence for scarring effects, it would be surprising if they are completely absent. However, even if there are long-term cohort effects, it remains uncertain if this would affect individuals with a general and vocational degree differently. The high unemployment might have been less detrimental for the careers of individuals with a vocational degree because they had a smoother transition to the labour market. On the other hand on could argue that they have weaker effects on the careers of workers with a general degree because they will be more flexible. If both mechanism work out at the same time the might cancel each other out, resulting in unbiased predictions but higher standard errors of the age effects of vocational specificity on the labour market outcomes.

The zero cohort assumption might also be violated when there are compositional differences between cohorts. Due to educational expansion academic education has become more popular over upper secondary—often more vocational specific—education. This might mean that recent cohorts of vocational students have become a more 'negatively' selected group. The ethnic composition also differs across cohorts. More recent cohorts consist of more immigrants. When, for example, migrants benefit more from more vocationally specific education (because it relies less on language skills), this might explain why especially younger people benefit from vocational education. However, by controlling for educational level and the ethnicity of respondents we

largely rule out these effects. All in all, we expect modest bias due to the assumption of a zero cohort effects and find it difficult to predict in what direction this bias would go when it concerns the difference between vocational and general graduates.

With the zero cohort effect assumption our age and period effect can be estimated. An interaction between the age and period is added to test to what extent life-cycle effects differ across periods. We emphasize that these life-cycle effects reflect the age effects of individuals that *choose* a certain type of education. They do not reflect the counterfactual scenario when the same individuals would have studied something else. As shown by Malamud and Pop-Eleches (2010) these selection effects can potentially explain the different outcomes between vocational and general graduates. Thus, the causal effect of general versus vocational education is most likely smaller than the effect that we present.

OLS regression models are used to predict job status. Logistic regression is used to predict the probabilities of being employed and being unemployed while searching for a job. Logistic regression models are criticized (Mood, 2010). However, the main advantage of logistic regression over linear probability models is that they often result in more reliable predicted probabilities, especially at specific points in the distribution (Mood 2010: p. 78; Chatla and Shmueli, 2013). In our case this is visible early in life. Linear and logistic regression on a sub-sample of respondents below 25 shows that individuals with a vocational degree are more often employed than those with a general degree. Logistic regression captures this effect, but linear probability models do not because a linear trend is forced upon the data. In all other models, logistic and linear regression resulted in highly similar results.

We estimate all models with robust and clustered standard errors within cohorts to account for the dependency in observations of respondents from a same cohort. The proportion variance on the period level was very low and does not significantly differ from 0 according to a likelihood ratio test, and hence in our models we did not account for this clustering.

Our estimation procedure is as follows: In Model 1 we include the effect of age, period, and vocational specificity (linkage strength, M_g). In line with previous research (e.g. Hanushek *et al.*, 2017; Forster and Bol, 2018) age is measured both as a linear and a quadratic term. Despite that a quadratic age (and period) effect results in a relatively complex model, it increases the model fit and results in more reliable outcomes because job status and employability follow a U-shaped curve over the life-cycle. In the instance of a logistic regression this U-shape is not entirely captured by the logit function. To give an example: leaving the squared effect out would provide us with estimations that suggest that youth unemployment is very low, something we know to be false. We have included a quadratic term for vocational specificity (M_g) as well, because being at the extremes of the general-vocational spectrum might result in the different labour market outcomes.

In Model 2, we add the interaction between age and vocational specificity. Only the interaction between the linear effect of vocational specificity and age is included to keep a somewhat parsimonious model (cf. Hanushek *et al.*, 2017; Forster and Bol, 2018). Vocational specificity is mean-centred—in all models—, so that the effect of age can be interpreted as the age effect for those with an average vocational specificity. Age is subtracted with 20, so that the effect of vocational specificity is the predicted effect for individuals aged 20—those at the start of their career. It is divided by 10 to ease interpretation.

In Model 3, we include an interaction between period and vocational specificity*age. To ease interpretation, period starts at zero (in January 1996), and every month .1 is added, so that the (main) effect of age and linkage applies for respondents at the start of our observation window. These relatively complex three-way interactions are graphically presented in marginal effects plots (the two way interactions are presented in Supplementary Appendix C and D). In these figures we compare respondents from an educational program with a weak linkage strength (1 standard deviation below the mean) to respondents from a strongly linking educational program (1 standard deviation above the mean).[2]

Results

Employment

The logistic regressions on employment are presented in Table 3, separately for men and women. For ease of interpretation linkage strength is standardized, age is subtracted by 20 and divided by 10. The three way interactions between age, vocational specificity, and period from Models 3a (men) and 3b (women) are graphically depicted in Figure 1. The predicted probabilities in Figure 1 can also help the reader to interpret the two-way interactions from Models 1a, 1b, 2a, and 2b.[3]

Model 1a shows that for men linkage has a positive effect on employment: the stronger the link between an educational program and the labour market (i.e. the more vocational specific), the greater the probability of being employed. A one standard deviation increase in our measure of vocational specificity increases the odds

Table 3. Logistic regression on having a job across the life-cycle and across time

	Men						Women					
	M1a		M2a		M3a		M1b		M2b		M3b	
Constant	−1.863	(0.114)**	−1.777	(0.114)**	−1.380	(0.106)**	−2.448	(0.107)**	−2.376	(0.110)**	−2.191	(0.129)**
Vocational specificity												
Linkage	0.150	(0.019)**	0.383	(0.025)**	0.416	(0.040)**	0.070	(0.010)**	0.239	(0.012)**	0.196	(0.023)**
Linkage squared	−0.005	(0.005)	0.012	(0.006)*	0.013	(0.006)**	0.051	(0.005)**	0.059	(0.005)**	0.058	(0.005)**
Age												
Age	1.883	(0.096)**	1.822	(0.094)**	1.676	(0.097)**	0.685	(0.097)**	0.654	(0.098)**	0.582	(0.109)**
Age squared	−0.549	(0.021)**	−0.537	(0.021)**	−0.542	(0.019)**	−0.274	(0.022)**	−0.272	(0.022)**	−0.280	(0.020)**
Period												
Period	0.890	(0.145)**	0.889	(0.144)**	0.483	(0.150)**	0.891	(0.113)**	0.884	(0.114)**	0.717	(0.134)**
Period squared	−0.270	(0.076)**	−0.269	(0.075)**	−0.304	(0.078)**	−0.170	(0.050)**	−0.168	(0.051)**	−0.211	(0.053)**
Interactions												
Linkage * age			−0.087	(0.009)**	−0.095	(0.012)**			−0.071	(0.005)**	−0.072	(0.009)**
Linkage * period					−0.031	(0.046)					0.075	(0.027)**
Age * period					0.175	(0.032)**					0.113	(0.040)**
Linkage * age * period					0.006	(0.013)					−0.010	(0.010)
Control variables	yes		yes			yes		yes		yes		yes

*$P < 0.05$.

**$P < 0.01$ (two-tailed).

Standard errors in brackets.

Source: EBB 1996–2012.

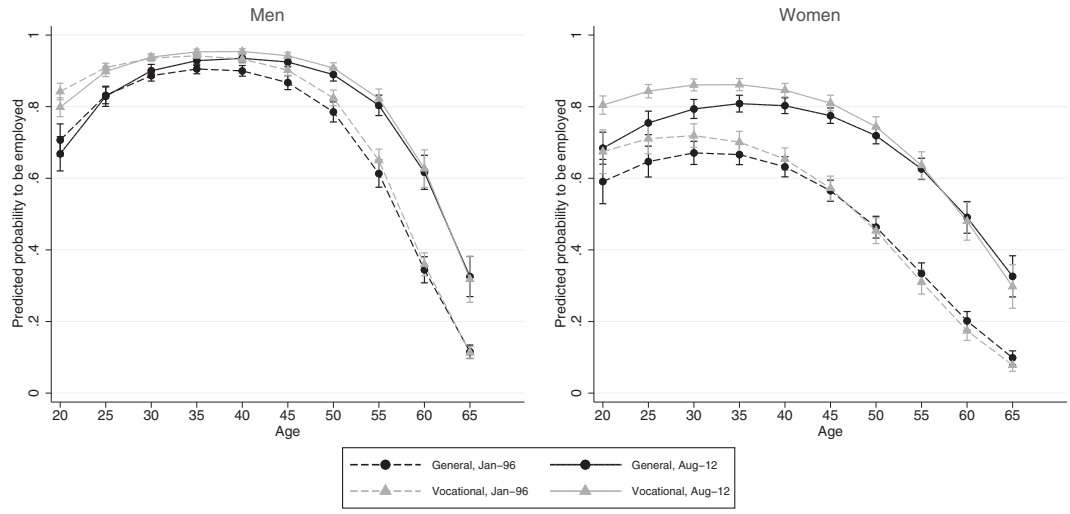

Figure 1. Predicted probabilities on the likelihood of having a job across the life-cycle and across time

Note: Bars present 95 per cent confidence intervals. General is defined as a linkage score one standard deviation below the mean, vocational is defined as a linkage score one standard deviation above the mean.

of being employed versus the odds of not being employed by 1.162 ($e^{.0150}$). Moreover, the effect is almost linear, as the predicted effect for the squared term is −0.005 and not significantly different from zero.

For women (Model 1b) we do find a curvilinear effect of linkage strength on employment. For individuals with a mean linkage strength our models predict that the odds of being employed versus the odds of not being employed increases by 1.073 ($e^{0.070}$), but this effect becomes stronger by 1.052 ($e^{0.051}$) for every standard deviation increase in linkage strength. Intuitively this means that our models predict that women that graduated from educational programs with high linkage are more likely to be employed, but this effect increases at the right tail: especially those from very strongly linking programs benefit. While the effects meet the conventional thresholds for significance, the effects are small in size (see also Supplementary Appendix B).

Model 1a and 1b indicate a curvilinear age effect on employment that is similar to other studies: both men and women are more likely to be employed at the start of their career, but their probability declines strongly as they grow older. With respect to period effects we find a curvilinear effect too: for men the odds of being employed versus the odds of not being employed increases with 2.435 ($e^{0.890}$) each month, but this effect becomes smaller by 1.310 ($e^{0.270}$) every month; while for women the odds of being employed versus the odds of not being employed increases with 2.438 ($e^{0.891}$) each month, but this effect becomes smaller by 1.185 ($e^{0.170}$) every month.

In Models 2a (men) and 2b (women) we add the interaction between our measure of vocational specificity (linkage strength) and age. The predicted interaction effect is negative and significantly different from zero for both men (−0.087) and women (−0.071). This confirms the results of earlier studies: there is a life cycle effect of vocational specificity on employment. Whereas it gives school-leavers a benefit over school-leavers with a more general degree, this benefit decreases in size over the career (see Figure 1).

Finally, in Model 3a and 3b we include the three-way interaction between age, linkage, and period to test whether the life cycle effects of vocational specificity change over time. Both for men (0.006) and women (−0.010) we find no evidence for a three-way interaction. The effects are not significant and close to zero. Contrary to what we would expect, life cycle effects seem to be relatively stable across time.

This also becomes visible in Figure 1, where we plot the predicted probability of being employed for individuals with a vocationally specific degree (one standard deviation above the mean) or a more general degree (one standard deviation below the mean). There is a clear difference in the probability to be employed for workers in 1996 (dashed line) compared to 2012 (solid line), but the difference in employment probabilities for workers with varying levels of vocational specificity remains surprisingly stable. For both periods, those with a more vocationally specific degree do better at the start of their career, and this benefit disappears later in the career. In contrast to earlier studies (cf. Hanushek *et al.*, 2017) we

do not find that workers with a more vocationally specific degree receive a penalty in later life. Rather, we find evidence for a convergence: later in the career it does not matter that much anymore what type of education one has attained (cf., Forster and Bol, 2018).[4]

Occupational Status

Table 4 follows the structure of Table 1, but has occupational status (ISEI) as the dependent variable. Models 1a and 1b show that both for men and women there is a quadratic age effect here as well: job status increases with age, but the slope of age flattens out. The effect on linkage is quadratic effect as well, for both men and women. Netting out the differences between educational levels and natives and immigrants, the linkage strength of an educational program is positively associated to job status, and this association is particularly strong for the strongest linking programs. Both for men and women, there is no significant time trend.

In Models 2a and 2b we include the interaction effect between age and linkage. For both men and women our models predict a negative interaction effect that is significantly different from 0. Figure 2 depicts this pattern graphically. For both men and women, at age 20 (dashed red line) the relation is curvilinear and those with very weak linkage and very high linkage have a relatively high predicted occupational status. Particularly those with a weak linkage and thus a general educational degree have a high job status, while those slightly above the mean (linkage around 0.5) are predicted to have the lowest job status.[5] For both men and women, the positive effects of having (very) specific skills decline as people grow older.

Models 3a and 3b include the three-way interaction between age, linkage, and period. For men, this three-way interaction is very small in size (−0.025) and not significantly different from zero. This means that again we find no evidence for a period effect: more generally schooled workers end up in higher status jobs, and this pattern has remained stable over time. For women, however, we do find a difference between 1996 and 2012 (−0.161). Women with a more general degree work in higher status job and this effect increases over the life course, but more so in later periods.

This pattern also becomes visible in Figure 3, that plots the average predicted job status for workers with a more general degree (−1*sd*) or more vocational degree (+1*sd*) for 1996 (dashed) and 2012 (solid). The first take-away from Figure 3 is that our models predict that workers with a more general degree end up in 'better' jobs, and this is found for both men and women. Second, the gap in occupational status grows over the career. Whereas early in the career the differences are small in size, later in the career the difference in job status between workers with a more general and more vocationally specific educational degree becomes substantial: 9 ISEI points and 6 ISEI points for respectively men and women.

The crucial question for our study is if this life-cycle effect can partly be attributed to period effects. For men, the answer is no. Having a vocationally specific degree is a penalty, and this penalty becomes larger when we look at job status. However, the pattern by which it does so is the same for 1996 and 2012. For women, we do find a (small) period effect. Figure 3 makes clear that the life-cycle penalty associated with a more vocationally specific degree is slightly larger in more recent periods. Particularly the job status of older women with a general degree has increased. It might be that a relatively large share of those women in the 1990s still worked in female dominated jobs with a relatively low job status, but in later periods a greater share of these women got more highly educated and increasingly worked in other sectors with a higher job status, like business or technology.

Robustness Checks

We have performed several robustness checks. First, using a linear probability model instead of logistic regression to predict the probability of having a job resulted in slightly different results. In the linear probability model, there was no employment premium to having a more vocational degree early in the career. When we selected people below age 25, however, a logistic and linear probability model did show that graduates with a more vocationally specific degree were more likely to be employed. This contradicts the finding from the linear probability model in which all ages groups are included, but is in line with the logistic regression model and previous studies (e.g. Hanushek *et al.*, 2017; Forster and Bol, 2018). All other effects are robust to using a linear probability and logistic regression.

Not controlling for period effects or replacing our measure of vocational specificity with a dummy indicating whether one has followed vocational (MBO and HBO) or general education (MAVO, HAVO, VWO, University) resulted in slightly stronger but further similar patterns (see also Supplementary Appendix C and D). However, controlling for cohort rather than period, resulted in lower predicted employment at younger ages, most likely because it takes into account that older cohorts were more likely to be unemployed around this age. In these models the life-

Table 4. OLS regression on job status across the life-cycle and across time

	Men						Women					
	M1a		M2a		M3a		M1b		M2b		M3b	
Constant	21.219	0.251**	21.201	0.250**	20.873	0.228**	17.686	0.306**	17.748	0.303**	17.852	0.275**
Vocational specificity												
Linkage	−2.418	0.095**	−1.496	0.091**	−1.728	0.105**	−2.747	0.101**	−2.295	0.083**	−2.657	0.119**
Linkage squared	1.228	0.021**	1.272	0.020**	1.269	0.020**	1.506	0.026**	1.513	0.026**	1.509	0.027**
Age												
Age	5.252	0.197**	5.140	0.185**	5.301	0.020**	2.342	0.268**	2.323	0.263**	2.281	0.200**
Age squared	−0.930	0.044**	−0.888	0.041**	−0.878	0.048**	−0.468	0.059**	−0.465	0.058**	−0.473	0.061**
Period												
Period	−0.122	0.257	−0.121	0.248	0.207	0.234	0.319	0.299	0.284	0.291	0.186	0.267
Period squared	−0.098	0.137	−0.103	0.130	−0.077	0.145	−0.156	0.164	−0.146	0.160	−0.180	0.179
Interactions												
Linkage * age			−0.450	0.026**	−0.431	0.043**			−0.231	0.018**	−0.062	0.045
Linkage * period					0.251	0.099*					0.365	0.077**
Age * period					−0.197	0.100					0.081	0.128
Linkage * age * period					−0.025	0.041					−0.161	0.035**
Control variables	yes		yes		yes		yes		yes		yes	

*$P < 0.05$.

**$P < 0.01$ (two-tailed).

Standard errors in brackets.

Source: EBB 1996–2012.

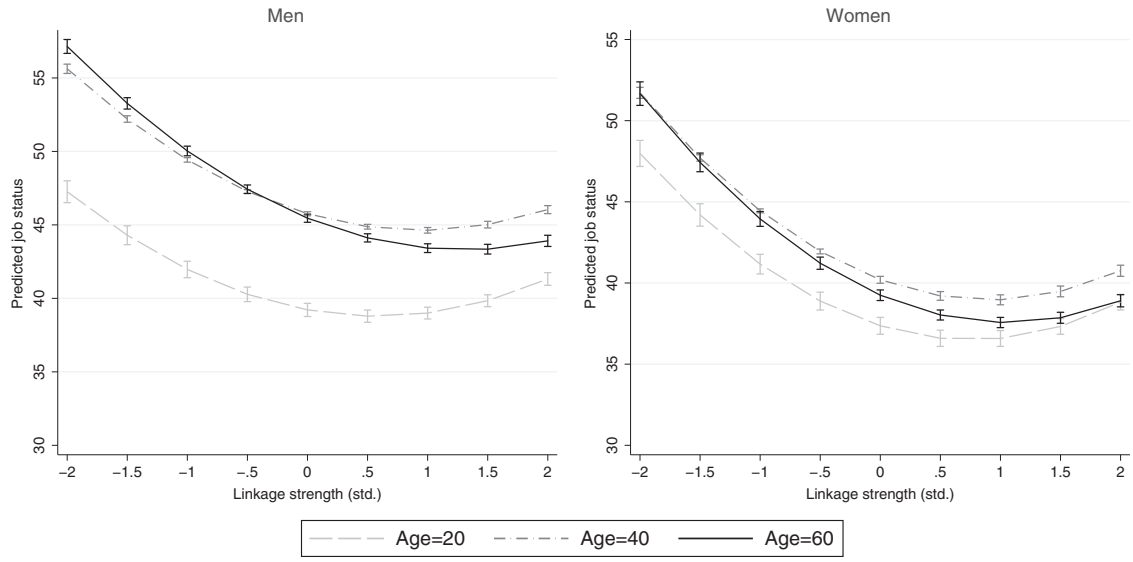

Figure 2. Predicted job status by linkage strength and age.

Note: Bars present 95 per cent confidence intervals.

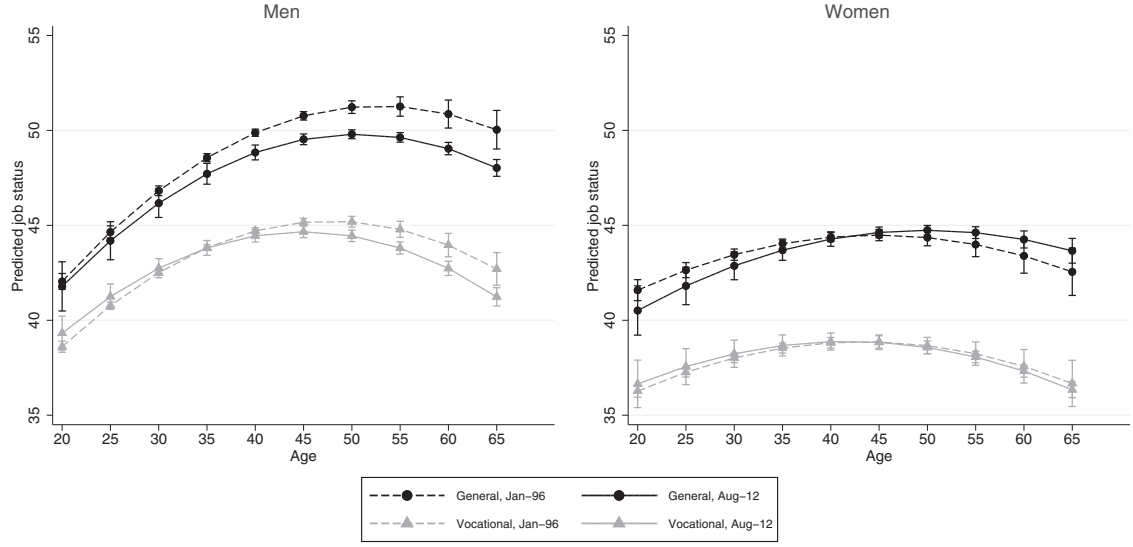

Figure 3. Marginal effects on job status across the life-cycle and across time (bars present 95 per cent confidence intervals).

Note: Bars present 95 per cent confidence intervals.

cycle patterns for those with a vocational and general degree do remain similar. In general, we find very similar results when controlling for cohort rather than period, indicating that the life cycle effects presented here did not differ much over the studied period.

Other robustness checks corroborated our conclusions as well. Including quadratic and cubic age, linkage and time effects (in a three-way interaction with each other) complicated our models but resulted in similar patterns. Adding controls for marital status and region (i.e. the Dutch provinces) resulted in similar results. A Heckman selection model to estimate the effects on job status, for whether one has a job or not, resulted in a difference on one crucial aspect from the presented results: where in models without a Heckman selection job status decreased after age 50, it did not decrease in the

Heckman model in which marital status was added in the second step and left out in the first step as exclusion restriction. Our main conclusions, however, remained similar. Because the outcomes of a selection model are fragile to a wrong specification of the exclusion restriction, we have decided to present the more conservative results. Note that the selection model only accounted the selection into employment, not the (most likely much more relevant) selection into a vocational or general degree. This means that we cannot rule out that our findings are caused by unobserved differences between those who enter a more vocational educational program and those who enter a more general educational program.[6]

Conclusion

In this study, we examined how labour market returns to a (vocationally) specific educational degree vary over the life cycle. Rather than making a binary distinction between vocational and general education we used a continuous indicator of the vocational specificity of educational programs, by looking at how strong they link to a set of occupations. Our assumption here is that programs with strong linkage, meaning that graduates with the same degree cluster in the same occupations, provided their students with more occupation-specific skills.

First, in line with earlier work we find that workers with a more vocationally specific educational degree make a smoother transition to the labour market. At the start of their career vocational graduates do enter jobs with a lower occupational status than general graduates. This means that vocational graduates enter the labour market more quickly, but do so in jobs that are less desirable.

Second, we find a trade-off between the early career advantages and late-career disadvantages of a vocational degree. This finding is in line with a developing literature on this theme (e.g. Brunello and Rocco, 2017; Golsteyn and Stenberg, 2017; Hanushek *et al.*, 2017; Forster and Bol, 2018). The initial employment advantage associated to vocational education declines as workers grow older. This catch-up appears around the age of 55/60 for men and women. This is roughly in line with earlier an Dutch study by Forster and Bol (2018), and slightly later than international findings from Hanushek *et al.* (2017) who found a catch-up around age 50. In addition, status advantages of general education, that were already visible at age 20, widened over the life-cycle. This is in line with a study of Korber and Oesch (2016) who report an earnings advantage of general education from age 30+, and Golsteyn and Stenberg (2017) who report earning advantages occurring earlier than age 30.

While we find a 'catch-up' when analyzing employment, we do not find that later in the career workers with a more general degree surpass workers with a vocational degree, as was suggested by previous studies (e.g. Hanushek *et al.*, 2017). For occupational status there is a life cycle effect as well. The initial lower job status associated to a more vocationally specific educational degree grows over the career, resulting in a late-career gap of around 7 points on the job status scale for men and women. To illustrate, this is similar to the difference in job status between a clerk (ISEI = 41) and a nurse (ISEI = 48). Our findings thus support the idea that the benefits associated to general education grow over the career.

Third, we investigated if period plays an important role in understanding the life cycle effects of vocational education. Earlier studies do argue this to be the case: the occupation-specific skills of vocational graduates will become obsolete particularly in times of rapid technological change. Moreover, in times of increasing flexibilization of the labour market those with a more rigid set of skills (vocational graduates) will be penalized harder than general graduates with their more flexible set of general skills.

We find very little support for this claim. The life cycle effects associated to a more vocationally specific degree did not change over time. For employment we find no difference at between the two extremes of our studied time period (1996 and 2012), nor for men or women. For occupational status we do find that the life cycle effect become slightly more prominent for women in more recent periods, meaning that female graduates from a more general educational program end up in more desirable jobs now than in earlier periods. However, the effect size is very small.

That vocational education remained more or less similarly (dis)attractive over time contradicts the idea that a general education is increasingly favourable in current times of technological change, outsourcing and flexibilization. The absence of an effect may be explained by a slower development of these factors than suggested in the literature (e.g. Autor, 2010; Brynjolfsson and McAfee, 2014; Hanushek *et al.*, 2017). It might also be the case that having vocationally specific skills has positive effects in periods where labour markets change rapidly, that might cancel out the theorized negative effects. For example, the demand for high quality manufacturing products has increased in recent years, while very specific skills are needed to make these products.

Overall, we find that controlling for period altered these results very little. Differences between general and vocational graduates over the life-cycle remained similar. Hence, it is unlikely that previous conclusions—

based on these patterns rather than exact predictions—are biased because either period or cohort effects are left out of the analytic model.

Is the reason we found no period effect due to the country under study? Our life cycle effects are largely in line with the results from studies on other countries, such as the United States. (e.g., Hanushek *et al.*, 2017), Britain (e.g. Brunello and Rocco, 2017), Sweden (Golsteyn and Stenberg, 2017), and Switzerland (Korber and Oesch, 2016). Moreover, over the past decades large technological changes have taken place in the Netherlands, and flexibilization of the labour market happened at an, international comparatively, very rapid pace. We are therefore sceptical that the reason why we found little evidence for period effects can be found in the country under study.

A number of limitations of our study have to be addressed. First, individuals might select themselves into different educational programs (Malamud and Pop-Eleches, 2010; Hall, 2016; Kirkeboen, Leuven and Mogstad, 2016). For example, individuals that want to learn vocational rather than general skills, or those who want to work in manual professions select themselves more often in vocational education programs. Unobserved factors might drive this selection, for example family of origin (Forster and Bol, 2018) or individual's cognitive skills and interests. In this study we could not account for both factors, and the effect of vocational education on job status might therefore partly reflect selection effects. This would mean that in the counterfactual scenario where vocational students would enrol into general programs instead, their long-term labour market prospects would not be affected. Second, to complicate it even further, this selectivity might change over time. For example, due to educational expansion the composition of educational levels have changed by which vocational oriented studies have become a more selective group. Third, drop-out rates are lower in vocational education, while (potential) drop-outs have relatively poor labour market prospects (Tessaring and Wannan, 2010). Hence, graduates from more general educational programs may be a more (positively) selected group, which can explain their higher job status. Due to these selection issues we are unable to make strong causal claims based on our analyses.

Irrespective of the limitations, our results show that the initial employment advantage associated to a more vocationally specific degree declines over the career. The initial disadvantage associated to job status grows for vocational graduates as well. We find clear evidence for life-cycle effects. These life cycle effects, however, hardly change over time. Our findings thus suggest that policies directed at increasing (youth) employment may benefit from smaller, more vocational oriented, educational programs, while policies that aim at life-long occupational progress may benefit from an emphasis on more general skills in education like mathematics, reading, and communication skills.

Notes

1 For example, Silverberg *et al.* (2004) base their findings on the influence of taking an extra vocational course, Wolbers (2007) and Iannelli and Raffe (2007) compare general and academic programs within a comparable level of education, and Roksa and Levey (2010) examines the effect of the extent to which a master program is linked to the labour market.

2 Educational programs that score 1 standard deviation below the mean are, for example, a gymnasium degree or a lower vocational education (MBO level 2) management. Educational programs that score 1 standard deviation above the mean are, for example, lower vocational education (MBO level 2) in construction or a PhD in management.

3 The predicted probability plots for these models can be found in Appendix B, C, and D.

4 While the employment rates of older workers may seem low, they are consistent with official statistics for the Netherlands. According to Statistics Netherlands, 60 per cent of the men aged 50–54 had a job in 1996, and 40 per cent of men between 55 and 59 (Statistic Netherlands, 2006). In 2012 these percentages were 79 and 47 per cent for men and 54 and 27 for women (Statistics Netherlands, 2018).

5 When we include an interaction between age and linkage, in which both age and linkage are a cubic effect, the positive effects of a more general educational program (e.g. linkage $= -3$) become weaker and similar to those of more vocational program (e.g. linkage $= 3$). This model is more complicated to estimate, so the standard errors increase. At a later age the results converge a pattern similar as presented in Figure 2.

6 We have split the results by educational level as well. It appears that the higher one's educational level is, the stronger vocational specificity is associated with a high job status and employment—as compared to a general education. This is exemplified by the comparative advantage of vocational oriented academic studies such as medicine or law. Thus, a general educational program may be particular beneficial for the lower educated.

Supplementary Data

Supplementary data are available at *ESR* online.

Acknowledgements

Thanks to Bas Hofstra and Nigel Kragten for their contributions.

Funding

This publication is part of the project "The Future of Craftmanship" and is made possible by a grant from the Programme Council for Policy-Oriented Education Research (ProBO) from the Netherlands Initiative for Educational Research (NRO) (grant 404-15-400). For more information on the project, see the website of ROA: http://roa.sbe.maastrichtuniversity.nl/"under research.

References

Acemoglu, D. and Autor, D. (2011). Skills, tasks and technologies: implications for employment and earnings. *Handbook of Labor Economics*, **4**, 1043–1171.

Arum, R. and Shavit, Y. (1995). Secondary vocational education and the transition from school to work. *Sociology of Education*, **68**, 187–204.

Autor, D. and Dorn, D. (2009). This job is "Getting Old": measuring changes in job opportunities using occupational age structure. *American Economic Review Papers and Proceedings*, **99**, 45–51.

Autor, D. (2010). *The Polarization of Job Opportunities in the U.S. labor Market: Implications for Employment and Earnings*. Washington, DC: Center for American Progress: The Hamilton Project.

Bell, A. and Jones, K. (2015). Age, period and cohort processes in longitudinal and life course analysis: a multilevel perspective. In Burton-Jeangros, C. *et al*. (Eds.), *A Life Course Perspective on Health Trajectories and Transitions*. Life Course Research and Social Policies 4. Springer Open.

Biavaschi, C. *et al*. (2012). *Youth Unemployment and Vocational Training. Background Paper for the World Development Report 2013*. Technical Report, Worldbank.

Bol, T. *et al*. (2019). School to work linkages, educational mismatches, and labor market outcomes. *American Sociological Review*, **84**, 275–307.

Breen, R. (2005). Explaining cross-national variation in youth unemployment: market and Institutional factors. *European Sociological Review*, **21**, 125–134.

Brunello, G. (2001). On the Complementarity between Education and Training in Europe. IZA Discussion Papers, No. 309. Bonn, Germany: Institute for the Study of Labor (IZA).

Brunello, G. and Rocco, L. (2017). The labor market effects of academic and vocational education over the life cycle. Evidence based on a British birth cohort. *Journal of Human Capital*, **11**, 106–166.

Brynjolfsson, E. and McAfee, A. (2014). *The Second Machine Age. Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: Norton.

Chatla, S. and Shmueli, G. (2013). *Linear Probability Models (LPM) and Big Data: The Good, the Bad, and the Ugly*. Indian School of Business Research Paper Series. Available at SSRN: https://ssrn.com/abstract=2353841 or http://dx.doi.org/10.2139/ssrn.2353841.

Cörvers, F. *et al*. (2011). High and Steady or Low and Rising? Life-Cycle Earnings Patterns in Vocational and General Education. ROA Research Memorandum ROA-RM-2011/7. Maastricht: Research Centre for Education and the Labour Market.

Cunha, F. and Heckman, J. (2007). The technology of skill formation. *American Economic Review*, **97**, 31–47.

Cutuli, G. and Guetto, R. (2012). Fixed-term contracts, economic conjuncture, and training opportunities: a comparative analysis across European labour markets. *European Sociological Review*, **32**, 1–14.

DiPrete, T. A. *et al*. (2017). School-to-work linkages in the United States, Germany and France. *American Journal of Sociology*, **122**, 1869–1938.

Forster, A. and Bol, T. (2018). Vocational education and employment over the life course using a new measure of occupational specificity. *Social Science Research*, **70**, 176–197.

Forster, A., Bol, T. and Van de Werfhorst, H. G. (2016). Vocational education and employment over the life-cycle. *Sociological Science*, **3**, 473–494.

Frey, C. B. and Osborne, M. A. (2017). The future of employment: how susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, **114**, 254–280.

Gangl, M. (2006). Scar effects of unemployment. An assessment of institutional complementarities. *American Sociological Review*, **71**, 986–1013.

Ganzeboom, H. B. J. and Treiman, D. J. (2010). *A New International Socio-Economic Index (ISEI) of Occupational Status for the International Standard Classification of Occupation 2008 (ISCO-08) Constructed with data from the ISSP 2002-2007*. Paper Presented at Annual Conference of International Social Survey Programme, Lisbon.

Golsteyn, B. and Stenberg, A. (2017). Earnings over the life course: general versus vocational education. *Journal of Human Capital*, **11**, 167–212.

Green, A. (2002). The many faces of lifelong learning: recent education policy trends in Europe. *Journal of Education Policy*, **18**, 611–626.

Green, A., Wolf, A. and Laney, T. (1999). *Convergence and Divergence in European Education and Training Systems*. London: Institute of Education.

Gregg, P. and Tominey, E. (2005). The wage scar from male youth unemployment. *Labour Economics*, **12**, 487–509.

Hall, C. (2016). Does more general education reduce the risk of future unemployment: evidence from an expansion of vocational upper secondary education. *Economics of Education Review*, **52**, 251–271.

Hampf, F. and Woessman, L. (2017). Vocational vs. general education and employment over the life cycle: new evidence from PIAAC. *CESifo Economic Studies*, **63**, 255–269.

Hanushek, E. A. *et al*. (2017). General education, vocational education, and labor-market outcomes over the life-cycle. *Journal of Human Resources*, **2**, 48–87.

Iannelli, D. and Raffe, D. (2007). Vocational upper-secondary education and the transition from school. *European Sociological Review*, **23**, 49–63.

Kirkeboen, L., Leuven, E. and Mogstad, M. (2016). Field of study, earnings and self selection. *Quarterly Journal of Economics*, **131**, 1057–1111.

Korber, M. and Oesch, D. (2016). *Does Vocational Education Give a Happy Start and a Lousy End to Careers? Employment and Earnings over the Life Course*. Geneva, Switzerland: Lives Working Paper 2016/ 57.

Krueger, D. and Kumar, K. B. (2004). Skill-specific rather than general education: a reason for US–Europe growth differences? *Journal of Economic Growth*, **9**, 167–207.

Leuze, K. (2007). What makes for a good start? Consequences of occupation-specific higher education for career mobility: Germany and Great Britain compared. *International Journal of Sociology*, **37**, 29–53.

Liu, Y. and Grusky, D. B. (2013). The payoff to skill in the third industrial revolution. *American Journal of Sociology*, **118**, 1330–1374.

Malamud, O. and Pop-Eleches, C. (2010). General education versus vocational training. Evidence from an economy in transition. *Review of Economics and Statistics*, **92**, 43–60.

Middeldorp, M. M., Edzes, A. J. E. and Van Dijk, J. (2019). Smoothness of the school-to-work transition. General versus vocational upper-secondary education. *European Sociological Review*, **35**, 81–97.

Mood, C. (2010). Logistic regression: why we cannot do what we think we can do, and what we can do about it. *European Sociological Review*, **26**, 67–82.

Nedelkoska, L. and Quintini, G. (2018). *Automation, Skills Use and Training*. Paris, France: OECD Social, Employment and Migration Working Papers: JT03428260.

Nilsen, Ø. A. and Reiso, K. H. (2014). Scarring effects of early-career unemployment. *Nordic Economic Policy Review*, **1**, 13–45.

Noelke, C., Gebel, M. and Kogan, I. (2012). Uniform inequalities: institutional differentiation and the transition from higher education to work in post-socialist central and Eastern Europe. *European Sociological Review*, **28**, 704–716.

Roksa, J. and Levey, T. (2010). What can you do with that degree? College major and occupational status of college graduates over time. *Social Forces*, **89**, 389–416.

Rosenbaum, J. E. *et al*. (1990). Market and network theories of the transition from high school to work: their application to industrialized societies. *Annual Review of Sociology*, **16**, 263–299.

Ryan, P. (2001). The school-to-work transition: a cross-national perspective. *Journal of Economic Literature*, **39**, 34–92.

Ryan, P. (2003). Evaluating vocationalism. *European Journal of Education*, **38**, 147–162.

Scherer, S. (2005). Patterns of labor market entry: long wait or career instability? An empirical comparison of Italy, Great Britain and West Germany. *European Sociological Review*, **21**, 427–440.

Shavit, Y. and Müller, W. (1998). *From School to Work. A Comparative Study of Educational Qualifications and Occupational Destinations*. Oxford: Clarendon Press.

Shavit, Y. and Müller, W. (2000). Vocational secondary education. *European Societies*, **2**, 29–50.

Silverberg, M. *et al*. (2004). *National Assessment of Vocational Education*. Washington, DC, USA: Final Report to Congress.

Statistic Netherlands (2006). Kwart werkzame beroepsbevolking is 50-plus (quarter workforce is 50-pus). CBS news-facts. Available from: https://www.cbs.nl/nl-nl/nieuws/2006/19/kwart-werkzame-beroepsbevolking-is-50-plus.

Statistics Netherlands (2018). Arbeidsmarktdeelname, kerncijfer. Available from: https://opendata.cbs.nl/statline/#/CBS/nl/dataset/82309NED/table?ts=1559123819293.

Stenberg, A. and Westerlund, O. (2015). The long-term earnings consequences of general vs. specific training of the unemployed. *Journal of European Labor Studies*, **4**, 1–26.

Tessaring, M. and Wannan, J. (2010). *Vocational Education and Training: Key to the Future*. Luxembourg: European Commission.

Van de Werfhorst, H. G. (2011). Skill and education effects on earnings in 18 countries: the role of national educational institutions. *Social Science Research*, **40**, 1078–1090.

Vogtenhuber, S. (2015). Explaining country variation in employee training: an INSTITUTIONAL analysis of education systems and their influence on training and its returns. *European Sociological Review*, **31**, 77–90.

Weber, S. (2014). Human capital depreciation and education level. *International Journal of Manpower*, **35**, 613–642.

Woessman, L. (2016). The economic case for education. *Education Economics*, **24**, 3–32.

Wolbers, M. H. J. (2007). Patterns of labor market entry: a comparative perspective on school-to-work transitions in 11 European countries. *Acta Sociologica*, **50**, 189–210.

Wolbers, M. H. J. (2016). A generation lost? Prolonged effects of labor market entry in times of high unemployment in the Netherlands. *Research in Social Stratification and Mobility*, **46**, 51–59.

Jesper Rözer is a Postdoctoral Research fellow at the Sociology Department at the University of Amsterdam. His research agenda revolves around the intersection of social networks, social inequalities, and health. His works have been published, among others, in *Social Science and Medicine*, *Social Science Research*, and *Social Indicators Research*. More information can be found at www.rozer.nl.

Thijs Bol is Associate Professor in the Department of Sociology at the University of Amsterdam and co-director of the Amsterdam Centre for Inequality Studies. His research focuses on inequality, stratification, occupations, and inequality in science. In his current work he investigates the transition from school to work from a country-comparative perspective. Another project tries to identify the causes of inequality in science funding. Recent publications include "School-to-Work Linkages, Educational Mismatches, and Labor Market Outcomes" (ASR, 2019), "The Matthew Effect in Science Funding" (PNAS, 2018), and "School-to-Work Linkages in the United States, France, and Germany" (AJS, 2017). More information can be found at www.thijsbol.com.