Social Science Research 70 (2018) 176–197

Contents lists available at ScienceDirect

Social Science Research

journal homepage: www.elsevier.com/locate/ssresearch

Vocational education and employment over the life course using a new measure of occupational specificity

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ARTICLE INFO

Keywords:
Vocational education
Labor market
Segregation indices
Linkage
Netherlands

ABSTRACT

Vocational education is seen as beneficial for the labor market allocation of young people. However, recent studies point to disadvantages later in the life course, where the specific skills that are obtained from vocational education decrease employability. This paper re-evaluates this hypothesis for the Netherlands with an improved measure for the vocational specificity of educational programs, utilizing both vertical (level) and horizontal (field) information on education. More specifically, we use a gradual measure for the linkage strength between education and occupation to predict employment over the life course. Using data from the national Dutch labor force surveys, we show that there is considerable heterogeneity in occupational specificity within the categories of vocational and general educational programs that is masked when using a dichotomous classification of general versus vocational education. In the life course analyses we find that the large early benefits of having vocational education disappear later in the career and turn into a small disadvantage before retirement.

1. Introduction

The preparation of youth for the labor market is a key responsibility of an educational system and education plays a major role in the distribution of life chances through this function. Previous studies have highlighted the importance of the vocationality of the educational system for allocating graduates in the labor market, finding that vocational education enhances the transition from school to the first job (Shavit and Müller, 1998; Müller and Gangl, 2003; Breen, 2005). The strong occupationally oriented training in vocational education systems has been praised by policy makers as an efficient way of lowering youth unemployment (OECD and ILO, 2014; Biavaschi et al., 2013). The suggested mechanism that explains why vocationally educated graduates find a job faster is that their occupation specific skills are immediately valuable for employers (Arum and Shavit, 1995).

Recent studies have suggested that the effect of occupation specific skills varies over the life course (Hanushek et al., 2017; Forster et al., 2016). This indicates the importance of taking a life course perspective and of looking beyond the immediate transition from school to the first job. The main finding of Hanushek et al. (2017) is that initial employment benefits of vocational graduates turn into disadvantages if one considers the whole labor market career up to the retirement age. Older workers with a vocational degree are less likely to be employed than older workers with a general degree. Their main explanation for this phenomenon – which they term life course vocational decline – is that over the career, specific occupational skills become obsolete faster than general skills if they are not adequately updated by on-the-job training. Vocational workers have a specific set of skills and are therefore less flexible than workers with a general educational degree.

Research on the school-to-work transition as well as on the hypothesis about life course vocational decline argues that the

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https://doi.org/10.1016/j.ssresearch.2017.11.004
Received 9 March 2017; Received in revised form 17 July 2017; Accepted 15 November 2017
Available online 22 November 2017
0049-089X/

occupational specificity of an educational program is the main mechanism through which vocational education influences labor market outcomes. However, both lines of research do not measure occupational specificity directly. Instead, they assume a dichotomy: vocational education leads to highly specific skills, and general education yields no specific skills. Following DiPrete et al. (2017), we argue that the vocationality of educational programs is gradual. Some vocational programs, like car mechanic training, might indeed convey very specific occupational skills, whereas for instance commerce oriented vocational programs might in fact rather teach general skills even though they are classified as vocational programs. The same argument can be made for educational programs that are classified as general. It is hard to argue that the occupational specificity of the study of medicine is similar to that of any social sciences major, although both are labeled as general education in conventional educational schemes.

Our main research question is as follows: *Do graduates from educational programs that are more strongly linked to certain occupational positions experience an initial advantage and subsequent disadvantage in employment probabilities compared to graduates from programs with lower occupational specificity?* In answering this question, we will contribute to the literature in two ways:

First, we will re-evaluate the life course hypothesis of vocational decline. So far, the decline has mostly been investigated with comparative survey data that contain only small samples for individual countries (Hanushek et al., 2017; Forster et al., 2016). In these cross-national data, the level of detail that is available about both the level and field of study of educational graduates tends to be low. For this study we rely on the Dutch Labor Force Survey (EBB), which contains highly detailed information about education and occupation. The Netherlands is a perfect case to test the life course hypothesis: it has a comparatively high enrollment in vocational education, with a similarly large dual system in which school and work are combined (Bol and Van de Werfhorst, 2013). If the life course hypothesis holds, we would expect to see differences in life course probabilities in employment for vocational and general graduates.

Second, we investigate the vocational decline hypothesis using an improved measure for vocationality. Instead of dichotomizing educational programs as vocational or general, this measure captures the occupational specificity of educational programs directly. Following DiPrete et al. (2017), we use the linkage strength between educational programs and occupational positions to measure the occupational specificity of single educational programs. We will not only focus on levels of education but also fields of study, given the importance of fields for the labor market success of school leavers (e.g., Kirkebøen et al., 2015). If, as the existing literature argues, occupational specificity is indeed the main mechanism through which vocationally schooled graduates gain a benefit when entering the labor market and suffer a penalty in later life, we should find these results especially with our more direct measure of occupational specificity.

Answers to the question of vocational decline are relevant to public debates about the value of vocational content of education. The generally positive evaluation of vocational education in the school-to-work transition leads to calls for more vocational elements in education and a tighter coupling of school and work place whenever youth unemployment is on the rise. However, such policies are only advisable if a highly occupation specific education does not revert into a disadvantage over the life course.

Our analyses yield two important findings. First, we find that the occupational specificity of educational programs is very poorly captured by using a dichotomous indicator of vocational versus general education – at least in the Netherlands. We find large heterogeneity in occupational specificity if we look *within* general or vocational programs at a given educational level. This is an important finding for the field, indicating that we need to rethink how the vocationality of educational programs is operationalized. Second, we only partially confirm the life course hypothesis. Having a highly occupational specific education degree generates an initial benefit, as occupational specificity is strongly associated with employment at the start of the career. This initial benefit decreases in later life, but in contrast to what earlier research suggested, we find that only very late in the career (after 60 years of age) having occupation-specific education becomes a penalty.

2. Vocational education and labor market outcomes

In the following section, theoretical arguments about labor market outcomes of vocational education are presented for (1) the school-to-work transition and (2) the further labor market career.

2.1. School-to-work transition

As already mentioned, vocational education is commonly found to be advantageous for the labor market allocation of graduates (e.g., Shavit and Müller, 1998; Müller and Gangl, 2003; Breen, 2005). Cross-national research has shown that in countries with a high proportion of vocational education, labor market entry is smoother (Shavit and Müller, 1998; Van der Velden and Wolbers, 2003; Breen, 2005; Wolbers, 2007). Some of these comparative studies find that vocational graduates indeed experience advantages compared to their peers with general training (Shavit and Müller, 1998; Scherer, 2005), while others conclude that the transition benefits also extend to other graduates in countries where vocational education is widespread (Iannelli and Raffe, 2007; Wolbers, 2007). There are several mechanisms through which educational programs become occupation specific and through which the benefits of vocational education may operate.

First, the most dominant explanation focuses on the type of skills taught in vocational education programs. Vocational degrees are beneficial for obtaining employment because of the specific skills that graduates have obtained (Arum and Shavit, 1995; Scherer, 2005; Wolbers, 2007; Van de Werfhorst, 2011). In vocational education, students are prepared for a very narrow set of occupations. Someone who learns the narrow technical skills to repair cars will most often end up working in an occupation where these skills can be put to use. In contrast to generally schooled workers, vocational graduates have skills that are immediately productivity-enhancing, thereby making them attractive for employers.

A second, related, mechanism emphasizes the signaling function of vocational degrees (Arum and Shavit, 1995). Irrespective of whether vocational graduates are really immediately productive, having an occupation-specific degree will pay off as long as employers believe that it is the case. Here, the focus is not on the skills which are actually obtained but rather on the productivity which an educational title signals to employers.

Although both mechanisms emphasize different aspects of a vocational degree, both strongly emphasize that vocational education is beneficial only when it conveys or signals narrow occupation-specific rather than broad skills. Broad vocational skills serve more as a safety net for low achievers and do not have the same benefits as occupation-specific training. They are above all a signal of low ability and the skills are not specific enough to replace on-the-job training (Shavit and Müller, 1998).

A country with a strong vocational system in which beneficial individual-level effects are expected, is the country under study: the Netherlands (Shavit and Müller, 1998). Indeed, De Graaf and Ultee (1998) find lower unemployment rates for vocational graduates compared to generally trained workers in the Netherlands. Following the argument about the individual benefits of vocational education for labor market allocation, we assume that, in the Netherlands, occupational specificity has a positive influence on employment probabilities in the school-to-work transition. This leads us to the following hypothesis:

H1. The occupational specificity of an educational program is positively associated with employment probabilities early in the career.

2.2. Life course

While the vast majority of studies investigates how vocational education affects the transition from school to the first job, there in an increasing number of studies that take a career-perspective. Even if vocational programs smoothen the transition from school to work, those advantages might decline over the life course (Hanushek et al., 2017). The expected mechanism behind this decline is the burden of having highly specific skills later in the career. Hanushek et al. (2017) argue that with technological change, the need for skills in the labor market has changed, and many skills that might have been useful at the start of the career became obsolete. Occupation-specific skills are advantageous when entering the labor market but, later in the career, they make workers inflexible when they have to move to a different job or occupation.

Hanushek et al. (2017) argue that on-the-job training is required to keep the narrow occupational skills of vocational workers updated over the course of their labor market career. Since employers are used to obtain fully trained workers from the educational system, they are often not prepared to invest much in further training. According to Hanushek et al. (2017), this problem is especially prominent in countries where vocational education is widespread and occupation-specific – like in the Netherlands. The changing demand caused by technological change and employers' low investment in on-the-job training leads to a decreasing value of vocational education. The central hypothesis of Hanushek et al. (2017) is that the initial higher employment of vocational graduates compared to general education graduates reverses in the later career, and having occupation-specific skills becomes a burden instead of a blessing.

Hanushek et al. (2017) find support for their hypothesis. Initial benefits of vocational education are reversed at a later point in the labor market career. The authors report that at an age of 16, vocational graduates are 7 percentage points more likely to be employed than individuals with general education but that this gap narrows subsequently and reverses into a disadvantage at the age of 50. Forster et al. (2016) largely confirm these results. They also find that the initial benefit turns into a disadvantage. However, in contrast to Hanushek et al. (2017), their results do not indicate that the *vocational decline hypothesis* is especially prominent in countries with a strong vocational system. Vogtenhuber (2014a) finds in his study of Austria that transitions in the labor market after the first entrance are less positive for vocational graduates than for generally educated individuals.

We evaluate the vocational decline hypothesis for the Netherlands. While Hanushek et al. (2017) focus on a comparative perspective and, thereby, necessarily apply less detail to the study of single countries, we use very detailed micro-level data which allow us to test the claims more thoroughly for one country. The Netherlands is a country with a strong vocational system and high enrollment in a vast number of specific training programs for which strong decline effects are expected. Our subsequent hypothesis is therefore:

H2. The positive association between occupational specificity and employment declines with age and having an occupation-specific educational degree becomes a disadvantage in the later career.

3. The measurement of occupational specificity

The hypotheses formulated in the previous section assume that occupational specificity is the mechanism through which education leads to beneficial labor market outcomes in the school-to-work transition and to a subsequent decline over the labor market career. In this section we will discuss how previous research measured whether an educational program was occupational specific or not, what drawbacks arise from this measurement, and how the operationalization can be improved by using a gradual measure of occupational specificity.

3.1. The traditional dichotomy

It is difficult to find a universal definition of vocational education, as it takes different forms in different countries: from firm-based training, to dual apprenticeships, to education in specialized schools and vocational curricula in regular high schools. Although there are different forms, scholars identify vocational education programs by the specificity of skills which they convey or by the closeness of their association with certain labor market positions.

The differentiation between general and specific skills originates from human capital theory (Becker, 1964). Specific skills are those which are immediately valuable within one occupation or even only in one firm, whereas general skills are broad and applicable in a variety of contexts. Shavit and Müller (1998) use the specific-general distinction as well, and further differentiate the specificity of skills into broad vocational skills, specific vocational skills and general skills. Broad vocational skills are entirely obtained in schools that most often serve as a safety net for low-achievers and which do not teach the skills for a specific occupation but rather general practical skills that can be applied in different occupations. In contrast, specific vocational skills are taught either in a dual system with firm- and school-based training elements (e.g. in Germany) or in specialized schools (e.g. in the Netherlands) that offer a wide array of different very specialized training programs for detailed occupational titles.

In their work, Shavit and Müller (1998) rely on the Comparative Analysis of Social Mobility in Industrial Nations (CASMIN) educational classification (Müller et al., 1989; Erikson and Goldthorpe, 1992). This is one of the major educational classifications used in comparative sociological research and it reflects the separation of general and specific skills which are taught in academic and vocational programs respectively. CASMIN uses a hierarchical differentiation of educational degrees (i.e., educational levels) as well as the orientation of a program within a level (general or vocational) (Müller et al., 1989). The original version of the CASMIN classification, developed in the 1970s, includes vocational degrees on elementary and intermediate educational levels. While Müller et al. (1989) acknowledge the difficulties caused by the high diversity of educational programs in different countries, especially on the intermediate level, they nevertheless decide for a dichotomous classification of vocational and general programs (König et al., 1988). A revision of the CASMIN scheme at the end of the 1990s - also using a dichotomous distinction between vocational and general - extends the classification of vocational programs to the tertiary education level in reaction to the development of professional degrees in the higher education sector (Brauns and Steinmann, 1997; Brauns et al., 2003).

The most common alternative to the CASMIN scheme is the International Standard Classification of Education (ISCED), developed by UNESCO. ISCED is a cross-nationally comparable classification of both educational levels and fields. Both in the 1997 and 2011 versions of ISCED, a dichotomous separation of vocational and general education on the (upper) secondary and tertiary levels of education is used. It defines vocational education as all those programs “that are designed for learners to acquire the knowledge, skills and competencies specific to a particular occupation, trade, or class of occupations or trades. Such programs may have work-based components (e.g. apprenticeships, dual-system education programs). Successful completion of such programs leads to labor market-relevant, vocational qualifications” (UNESCO Institute for Statistics, 2012, p.14). In contrast, general education programs are defined “to develop learners' general knowledge, skills and competencies, as well as literacy and numeracy skills” (UNESCO Institute for Statistics, 2012, p.14).

Virtually all research in the field of education and comparative stratification relies on one of these two classifications to distinguish vocational from general education. This means that virtually all previous attempts to define the occupational specificity of educational programs relies on a dichotomous classification between either specific skills (vocational), or broad skills (general), with very few exceptions (Vogtenhuber, 2014b; DiPrete et al., 2017).

3.2. *Beyond the dichotomy: occupational specificity*

The current state of the art is that programs that are classified as vocational are specific and that programs that are classified as general are not specific. We argue that it is unlikely that all programs which are classified as vocational entail the exact same occupational specificity. The same can be argued for general educational programs: they will be heterogeneous in their occupational specificity. We believe that this makes the dichotomous measure unsuitable for capturing the varying degree of vocationality of educational programs, especially when one is interested in the occupational specificity of an educational program as the driving mechanism for labor market outcomes. This shortcoming of the dichotomous approach to the measurement of vocationality shows the necessity for a measure that more directly captures the gradual nature of the occupational specificity of educational programs.

DiPrete et al. (2017) introduce such a gradual measure of vocationality. In their approach, occupational specificity is evaluated for single educational programs defined both by level and field. Instead of creating two groups within a level (vocational and general), their measure allows for heterogeneity between educational programs that have different levels and fields. DiPrete et al. (2017) coin their method a *linkage approach*, as it expresses the strength of the link between an educational program and a (set of) occupation(s). Occupational specificity of an educational program is high if a large number of graduates with that specific combination of level and field cluster in a narrow set of occupations. The occupational specificity of an educational program is low if graduates spread out over a large number of different occupations. Most university students in medicine become physicians, which means that the occupational specificity of that level and field combination (tertiary, medicine) is very high. Students of sociology at a university, in contrast, spread out over many more different occupations, and the linkage of this educational program is low.

DiPrete et al. (2017) argue that their measure of linkage strength is a good indicator for the occupational specificity of an educational program. When there is a weak link, and graduates spread out over many occupations, apparently the educational program provides a low level of occupation-specific skills. If the link is strong, and graduates cluster in one, or only a few occupations, this indicates that students in this occupation share knowledge and skills that are best utilized in one (or a few) occupations. While students from medicine and sociology clearly differ in the occupational specificity of the skills that they acquire, in the traditional dichotomous operationalization, students from both of these fields would be classified as having general education as they both attended university.

In this article, we rely on this linkage measure as our indicator for the occupational specificity of educational programs. This measurement uses a segregation approach (Reardon and Firebaugh, 2002; Mora and Ruiz-Castillo, 2011; Alonso-Villar and del Río, 2010; Frankel and Volij, 2011) which is based on the concept of entropy. In the context of measuring the association between educational level-fields and occupations, entropy reflects the amount of information that is gained about the occupational position of an individual if their educational degree becomes known. As someone's education is expected to contain some information on one's occupation, entropy within an education should be lower than overall entropy. Knowing someone's education should, therefore, lead to a reduction of entropy. While a more technical description of the measure will follow below, intuitively it should be clear that this reduction in entropy indicates the association between education and occupation, and that we will use this to measure the occupational specificity of educational programs in the Netherlands. With this gradual occupational specificity measure, the questions concerning education and labor market outcomes, which were presented in Section 2, will be re-evaluated.

4. Data

The Dutch Labor Force Survey (*Enquête Beroepsbevolking*, EBB) offers high quality micro-level data on educational levels, fields, and occupations (all required to calculate the occupational specificity of educational programs).[1] Moreover, it is the main source for Dutch labor force statistics and thus provides reliable information on the employment of respondents. Since the sample is large, we are able to investigate labor market outcomes for people of different age. The survey is administered as a rotating panel study of households: each month, a new representative sample of households in the Netherlands is drawn. Per household up to eight persons from the age of 15 can participate in the survey. Each respondent in the sample is then approached for five consecutive interviews over a period of twelve months.

We use the EBB rounds from 2010 to 2012. To achieve a sample size capable of precisely measuring linkage strength for a high number of educations and occupations, observations for these three years are pooled for the analyses. In these three years, the Dutch labor market has been quite comparable. Additionally, we include fixed effects for the survey year in each model to account for differences in overall employment. Only one observation per person is selected for the analysis.[2]

Different restrictions are made to the sample for the calculation of the linkage strength (the occupational specificity) and for analyzing the effect of occupational specificity on employment.

First, for the calculation of the linkage strength all respondents are included who have complete data on their highest educational degree and on their current labor market position, and who are not enrolled in education at the time of the interview. This means that the calculation of linkage strength is only carried out for individuals who are currently in employment as otherwise, no occupational data is available for them. Additionally, we only include respondents at the beginning of their career in the calculation of the linkage strength as we aim to calculate a measure for the link between education and job in the early career. If we included older workers as well, this might confound occupational mobility and school-to-work linkage. Similar to DiPrete et al. (2017), we select individuals who are within 15 years from the typical age of school completion for their respective educational level. Depending on their educational degree, these individuals are between 16 and 42 years old.[3] The final sample for the calculation of linkage strength has a size of 54,037 respondents. For calculating the linkage strength we do not split our sample by gender (see DiPrete et al., 2017).

Second, in our analyses of life course outcomes, we include individuals who are in a typical working age of 16–65 years old. This selection follows previous research on the life course effects of vocational education (Hanushek et al., 2017; Forster et al., 2016). Labor market outcomes are investigated for all respondents no matter their employment status. Again, respondents are excluded who are in education at the time of the survey as the focus of interest lies on individuals who have left full-time education and are either active in the labor market or out of employment for other reasons than education. This selection leads to a final sample of 214,752 respondents, whereof 106,445 are men and 108,307 are women. Now, analyses are carried out separately for men and women.

5. Variables

5.1. Occupational specificity

As occupational specificity is fundamentally about an association between education and occupation, two variables are necessary for its calculation: a detailed indicator for education and a detailed indicator for occupation.

In the EBB, educational degrees are measured by the Dutch educational classification (Standaard onderwijsindeling, SOI) which is oriented towards educational levels and fields in the Dutch educational system.[4] Each educational program is identified by a six-digit code in which the first two digits represent the level of education and the four remaining digits indicate the field of study. The two

[1] The EBB has a scientific use file which can be downloaded by researchers. For this article, however, we used a much more detailed and complete file that can only be accessed via Statistics Netherlands (Centraal Bureau voor de Statistiek, CBS).

[2] The first interview with complete data is selected for each respondent. Usually the first interview took place in wave 1 of the survey. However, if in that interview data of the individual was missing on one of the variables of interest, the first wave with complete data was used. Some individuals participated in the survey in two of the years. In this case, the first complete wave of the first year was selected. This also leads to the fact that a significantly higher proportion of the sample comes from the survey year 2010. Our results remain the same if we do not pool the three years.

[3] The different degrees in the Netherlands have different school-leaving ages, which can be found in Fig. A1. To each of these school-leaving ages 15 years is added to get the age range over which we have calculated the local linkage score. For example to obtain level 70 one finishes VWO with 18 and takes an additional 9 years to go through higher education, making 27 the regular school leaving age. To this age 15 years are added to end up at 42. Of course, individually not all respondents finished at the regular school leaving age. However, a span of 15 years should also be enough time for late school leavers to start their labor market career.

[4] A short overview of the Dutch educational system is presented in Appendix A.

digits for the level of education are further separable into the main level (first digit) and a sub-level within the main level (second digit). The four digits for the field of education work in a similar way. We use only the first two digits for the field in order to avoid empty cells. By truncating the SOI code, a four-digit code for educational levels-and-fields is obtained: the first two-digits indicate the level and sub-level and are followed by another two digits which represent the major field plus one level of sub-fields. The data contain 357 educational level-field combinations if we use this level of detail. Our sample of young workers with which we calculate linkage strength contains 325 different level-field combinations.

Occupational information is available in the EBB via the International Standard Classification of Occupations (ISCO) 2008. ISCO codes are four-digit numbers which represent four levels of detail for occupational categories. The first digit of the ISCO code displays the major occupational group, the subsequent digits symbolize sub-fields within these major groups. We use the first three digits of the ISCO codes. This decision addresses the trade-off between including detailed information and having enough cases per occupation available for the analysis. Following previous research, occupations within the military (major ISCO group 0) are excluded from all analyses as those categories are hard to compare with civil occupations (Weeden, 2002; Bol and Weeden, 2014). This selection results in 128 occupational categories for the segregation analysis.

As mentioned in Section 3.2, the measurement of occupational specificity is based on a segregation index, more specifically the Mutual Information Index (*M*) (DiPrete et al., 2017).[5] The *M* index calculates the total linkage strength of an educational system and is thus an aggregate characteristic. More precisely, it is the weighted sum of the linkage strength of all separate education programs, where the size of the educational program (the number of graduates) is the weight.[6] This linkage measure for all separate educational programs (defined by level and field), which expresses the strength of the contribution of that educational program to the occupational structure, is called the local linkage (M_g). This local linkage - our measure of occupational specificity - can be derived from equation (1).

$$M_g = \sum_j p_{j|g} ln\left(\frac{p_{j|g}}{p_j}\right) \tag{1}$$

In Equation (1), $p_{j|g}$ is the conditional probability of being in a certain occupation *j*, given one has the educational degree *g*. Remember that the educational degree is defined both by level *and* field. This value is multiplied by the logarithm of the ratio between the conditional probability $p_{j|g}$ and the unconditional probability p_j of being in that specific occupation *j* for the full working population. The result is then aggregated over all occupations to obtain the local linkage for one specific educational degree. Intuitively, local linkage will be very low if the distribution of workers with a specific degree is the same as the overall distribution of workers over occupations: apparently then the educational degree is not at all predictive of the occupation(s) workers end up in. Local linkage will be high if the conditional probability is much higher than the unconditional probability, as then education is strongly predictive of the occupation(s) where workers with that degree cluster in. A more technical discussion of the properties of the local linkage measure and the Mutual Information Index can be found in DiPrete et al. (2017) and Mora and Ruiz-Castillo (2011). In this article, we refer to local linkage as the occupational specificity of educational programs.

Equipped with the educational and occupational categories from above we have now enough information to calculate occupational specificity using equation (1). However, before doing so, we need to address a further issue: sample size in the single categories. Sparse cells (i.e. educational categories with a low number of observations) potentially inflate the occupational specificity value as single outliers have a high impact on the measure if categories are small. For instance, if there are only 10 individuals in an educational category, two individuals which randomly end up in the same occupation already constitute a high proportion in such an educational category compared to a cell with several hundreds of observations. Therefore, the potential for occupational specificity is negatively correlated to the number of respondents in an educational category. For this reason, DiPrete et al. (2017) require each educational level and field to have at least 100 observations. We analyzed how the cell size of educational categories affects the robustness of the occupational specificity measure.[7] Ideally, we would analyze large samples of individuals in each educational category. However, given sample restrictions, our additional analyses show that a cut-off of 100 observations per category, as chosen by DiPrete et al. (2017), is appropriate.[8]

Following this cut-off, educational level-field combinations with a cell size below 100 are identified, and are aggregated to a less detailed level by re-coding the fourth digit (the second field digit) into zero and thus setting the specific field to *Other*, only leaving information about the broader field (the first field digit). This re-coding results in a reduction from originally 315 level-fields to 192 remaining level-fields. The procedure is repeated for categories which still remain below the threshold so that the first field digit is

[5] Compared to previous attempts to measure occupational specificity with another segregation index – the GINI index (Allen et al., 2000; Vogtenhuber, 2014a) – *M* has the advantage of being strongly decomposable. This means that it can be used to measure the specificity of single educational programs but it also can serve as an indicator of the specificity of national educational systems.

[6] This means that if an educational program is strongly linked to an occupation but its size is minor, it contributes less to the overall linkage in a country than if the category is bigger. For example, a PhD in medicine is highly specific but only a few individuals obtain this degree. Therefore, the contribution to national vocationality is low.

[7] These additional analyses are available upon request from the first author.

[8] Additionally, we did all analyses with a cut-off of 120 observations. Although this leads to a smaller number of educational categories that can be analyzed, the results for the further analyses of vocational decline remain the same. We also did analyses where we used the full sample of workers 16-65 years old instead of only young workers to increase the sample size and thereby the number of educational categories with more than 100 observations. With this more powerful but theoretically less precise estimation of the linkage score, we find the same results.

also removed. After this procedure, 138 level and field combinations are left.[9] This re-coding leads to a loss of detail but allows us to leave those observations in the sample without subjecting them to sparse-cell bias. Nevertheless, the interpretation of the *Other* categories is less intuitive than for the remaining level-fields as they are necessarily broader in their content. In the unweighted sample of 241,683 observations, 12.2 percent are coded in a broader field than we have information for.[10]

Finally, occupational specificity is calculated for each educational category (four digit code) using equation (1), where the 138 educational programs are associated to the 128 occupational categories.[11] For our analyses we used the weights that are delivered with the EBB. We rescaled the sampling weights so that the sum of all weights equals the total number of observations. Although we discuss our results in more detail below, Appendix B shows that there is substantial variation in the occupational specificity of educational programs: The resulting linkage strength index ranges from 0.39 to 3.44 with an overall mean of 1.27 (SD = 0.62).[12]

5.2. *Other variables*

In our investigation of the association between occupational specificity and employment, we use several other (control) variables. Summary statistics of all variables for the regression sample are displayed in Table 1.

The dependent variable in the regressions is a binary measure of the employment status of individuals. Similar to Hanushek et al. (2017), we do not distinguish between different reasons for not working. Respondents who are coded as 0 can be unemployed in a narrow sense but it is also possible that they have left the labor force for reasons like retirement, inability to work, and so on. The main reason to keep all of these respondents in the reference category is that vocational education might not simply drive older workers into unemployment, it might make them leave the labor market altogether.[13]

The main independent variable is the occupational specificity of each level-field combination that was obtained in the analyses described in the previous section. This occupational specificity is measured at the level of educational programs and is matched to the individuals using their highest attained educational degree as identifier.

Age is the other main independent variable since it will be used to determine how the effect of local linkage on employment varies across the labor market career. The age range is defined by the sample restrictions outlined in Section 4, which means that we only observe individuals until they are 65 years old – the legal pension age in The Netherlands.

In our models we control for several factors. First, we know that educational level is both correlated with employment and occupational specificity, so it is of utmost importance to control for the level of education. This means that the predicted effect of occupational specificity is a *within* educational levels effect. We use the ISCED classification of educational levels to obtain an ordinal variable with 7 categories (added as a series of dummy variables).

A second control variable is region, given the potential regional effects on both the employment situation and the educational programs that students select. Finally, we also add a set of dummy variables for the three different survey years, to single out differences in employment in the three years of the EBB that were pooled for the analyses.

6. Methods

We estimate linear probability models with the dichotomous measure of employment status as dependent variable. An obvious alternative would be to estimate logistic regression models. Given criticism on the interpretation of interaction effects in logistic models, however, we decided to employ linear models instead (Ai and Norton, 2003; Norton et al., 2004). The results are very similar. In the logistic regressions the negative effects for occupational specificity at the end of the career are slightly less pronounced, but since we estimate a large number of interactions in our models, we prefer linear probability models.

Our control variables educational level, region, and survey year are added to all our models. The sampling weights provided by the EBB are also used for all models. Similar to all other studies that investigate the life course effects of occupational specificity, we run our analyses separately for men and women (Hanushek et al., 2017; Forster et al., 2016; Korber and Oesch, 2016). The employment patterns and labor market careers of men and women differ considerably due to structural gender inequalities and still existing traditional gender roles. Therefore, it is expected that their life course outcomes on the labor market differ in a way that is hard to control for in a joint analysis. Additionally, separate analyses may give interesting insights in differences between men and women when it comes to the influence of linkage strength on employment.

We mirror our analyses to previous studies which have investigated changes in returns to vocational education over the career in the following way: Employment is predicted by occupational specificity, age of the respondent and an interaction between these two variables. The main interest is then in this interaction effect, since it allows to assess whether the effect of having an occupation-specific educational degree on employment differs at different ages across the labor market career (Hanushek et al., 2017; Forster

[9] If we use the full sample for the calculation of the linkage strength, we can analyse 194 level-field combinations at a minimum cell size of 120 observations.

[10] Of course this fraction is lower if we use the full sample to calculate linkage (2.6 percent). To see whether our results also hold when we only look at the fully specified fields without the broader categories, we did all analyses excluding the recoded fields. The results stay the same. Therefore, in the main analyses all observations are used, also those who only have information on a broader field of study.

[11] The final list of all educational level-field combinations with their linkage strength and all occupational categories can be found in Appendix B.

[12] These are the unstandardized values of linkage strength. Since we estimate the regressions separately by gender, for those analyses we also standardize linkage strength for men and women separately.

[13] Further studies could address a possible difference between being unemployed and being out of the labor force in the context of linkage strength. This is, however, beyond the scope of this paper.

Table 1
Descriptive statistics for the full regression sample.

Variable	Values/Range	Men			Women		
		Obs.	Mean	SD	Obs.	Mean	SD
Employment status	0–1	106,445	0.81	0.39	108,307	0.68	0.47
employed	1	86,042			73,660		
unemployed	0	20,403			34,647		
Age	16–65	106,445	43.71	12.77	108,307	43.67	12.76
Linkage strength	0.39–3.44	106,445	1.31	0.59	108,307	1.22	0.62
Vocational education	0–1	106,445	0.67	0.47	108,307	0.66	0.47
vocational	1	71,425			71,768		
general	0	35,020			36,539		
Level of education	1–7	106,445	4.30	1.35	108,307	4.21	1.34
pre-primary	1	1647			1761		
primary	2	6479			7399		
lower secondary	3	21,569			23,507		
upper secondary	4	39,875			41,118		
post-secondary	5	3366			3251		
tertiary	6	32,769			30,910		
doctorate	7	740			361		
Region	1–12	106,445			108,307		
Groningen	1	3595			3632		
Friesland	2	4173			4117		
Drenthe	3	3133			3150		
Overijssel	4	7121			7181		
Flevoland	5	2526			2585		
Gelderland	6	12,704			12,960		
Utrecht	7	7635			8096		
Noord-Holland	8	17,352			17,779		
Zuid-Holland	9	22,414			22,910		
Zeeland	10	2535			2580		
Noord-Brabant	11	16,024			16,039		
Limburg	12	7233			7278		
Year	2010–2012	106,445			108,307		
2010	2010	49,864			50,326		
2011	2011	32,006			32,806		
2012	2012	24,575			25,175		

Note: Sampling weights are applied.
Source: EBB 2010–2012, own calculations.

et al., 2016; Korber and Oesch, 2016). A negative interaction effect symbolizes a decline of employment probability for vocationally trained workers with increasing age, and, thereby, would be an indicator for vocational decline.

This interaction with age is the only way to test the life course hypothesis with cross-sectional data. This also means that studies with cross-sectional data are not able to disentangle age effects from cohort effects which would be a worthwhile endeavor for future studies on the topic. Similar to Hanushek et al. (2017), the implicit assumption in our analyses is therefore “that conditional selectivity into education types does not vary over time” (p. 50). This is a strong assumption, as it is likely that the school-to-work linkages that graduates faced in the 1960s were different from what they are now. Yet, in our analyses, we have to assume that graduating from a particular educational program leads to the same local linkage score nowadays as it did several decades ago. In Appendix C we investigate this issue more closely, by calculating the local linkages for three subgroups: 16–35 year olds, 36–50 year olds, and 51–65 year olds in our sample. We find that there is a substantial difference between the first groups, but the latter two groups are – on average – very similar. This indicates that, although the linkage score is stronger for younger workers, cohort differences seem to be much smaller. Irrespective, future research should address the age-cohort issue more systematically by using panel data.

Similar to Hanushek et al. (2017), we use cross-sectional models. However, we make two important improvements to the model. First, as already discussed in detail, we will measure occupational specificity with our linkage measure instead of a dummy variable. Second, we account for the possibility of non-linear effects; both non-linearity in the age effect on employment but also non-linearity in how the effect of vocational education changes with age. We evaluate different functional forms by adding a different number of age terms in our models. We start with a model that only includes age, age squared and an interaction between age and occupational specificity, and resembles models from previous studies. Subsequently, we also add an interaction between age squared and specificity and in following models higher order age terms (age^3, age^4, etc.) and interactions between all those age terms and occupational specificity. We compare the models using indicators of model fit and by looking at the significance of the age and interaction terms in the models. Additionally, we compare margin plots of our models with a descriptive graph of the data to evaluate whether the prediction fits the data pattern reasonably well. The analyses on model fit are available upon request. These analyses show that a model including age terms up to age quartic and interactions of these age terms with occupational specificity fits the data best. This is

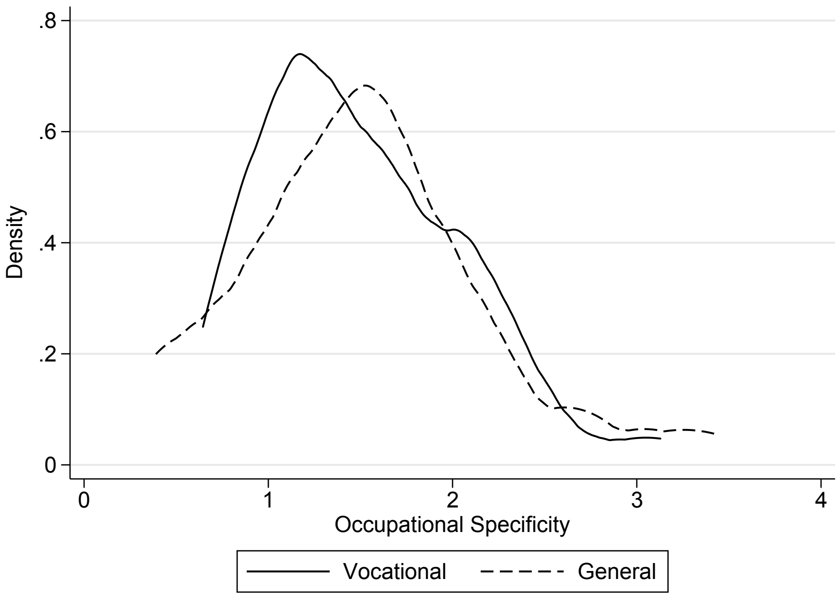

Fig. 1. Occupational specificity of vocational and general programs.

the main model we are going to discuss in the results section. Adding quadratic, cubic and quartic age terms does affect the predicted pattern, and allows for more flexibility for the life course effect of vocational education. We will compare our preferred model with the simpler model that was used by previous research and which only includes age, age squared and an interaction between age and occupational specificity. As the interpretation of regression coefficients with such a multitude of terms is very unintuitive, we are mostly relying on marginal effects and predicted probabilities in the discussion of our main results.

7. Results[14]

Before we turn to the multivariate results, we will discuss the descriptive characteristics of our measure of occupational specificity, and will show how much variation there is within vocational and general education.

7.1. Vocational education and occupational specificity

Fig. 1 shows kernel density plots for the occupational specificity of educational programs that are in the standard dichotomy characterized as vocational (solid line) or general (dashed line). Educational programs are coded as either general or vocational using the Dutch Educational Classification (*Standaard Onderwijsindeling*, SOI).[15]

The first finding from Fig. 1 is that vocational and general education are not that different concerning their occupational specificity. Average occupational specificity of vocational programs (mean = 1.515) and general programs (mean = 1.518) does not differ significantly (two-sided t-test: $t = 0.029$, $p = 0.9773$). The variation in occupational specificity is relatively similar between the two categories: there are “vocational” programs that are not occupation-specific at all (left side of the x-axis), just like there are “general” programs that are highly occupational specific (right side of the x-axis). While most literature assumes that the dichotomous distinction between vocational and general programs captures (average) differences in occupational specificity quite well, the figure indicates that – at least for the Netherlands – this is not the case.

The second finding from Fig. 1 is that there is a lot of heterogeneity *within* the two categories. The variation within the two categories is much larger than the average difference between them. This means that in order to understand how occupational specificity affects labor market outcomes, we need to look beyond a dummy-indicator for vocational or general and take this heterogeneity into account when measuring occupational specificity.

In Table 2 we take a closer look at the occupational specificity of (selected) educational levels and fields that are classified as general or vocational. While there are quite a few general educational programs that have a low occupational specificity, we can also see that the educational programs with the highest occupational specificity are general: *Law, Public Administration* (specificity = 3.07) and *Health Care* (3.44), both on the doctorate level. From the law program, about 62 percent of students become a *Legal*

[14] Replication files to reproduce all our analyses and results can be found on the authors' websites.

[15] On the lower secondary school level all programs are coded as general if the field is general (VMBO programs). All other programs are coded as vocational (mostly MBO level 1 programs and so-called Praktijkonderwijs). On the upper secondary level, HAVO and VWO programs are coded as general, all other programs (MBO) as vocational. On the tertiary level, HBO programs (short programs, professional Bachelor degrees) are coded as vocational, all other programs (BA, MA and Doctorate at universities) are coded as general.

Table 2
Examples for Strong and Weak linking Educational Categories.

	General	Vocational
Low Specificity	Upper Secondary Preparatory Academic Track (VWO),	HBO short program Commerce
	Upper Secondary Higher General Continued Education (HAVO),	MBO-4 program Commerce
High Specificity	Doctorate Law & Public Adminstration	MBO-4 program Health Care and Community Services
	Doctorate Health Care	MBO-3 program Public Order and Safety

Professional (ISCO category 261) and another 13 percent become *Regulatory Government Associate Professionals* (ISCO 335). From the health care program, 74 percent of students end up being *Medical Doctors* (ISCO 221) with all other occupations staying far below 10 percent.

The weakest linking general education programs are the general educational programs in upper secondary education with *HAVO* having a value of 0.39 and *VWO* with a local linkage of 0.45. From these programs, graduates spread out across a high number of occupations with single occupations receiving no more than 10 percent of graduates.

In the right panel of Table 2 we show selected educational programs that are classified as vocational. Among the vocational programs, again, especially health care and law programs are very occupation specific. For example graduates from MBO-3 programs in *Public Order and Safety* (local linkage = 3.118) are most often found in ISCO 541 (*Protective Service Workers*) with 46 percent while all other occupations receive much lower percentages. Those who are in *Health Care and Community Service* programs on the MBO-4 level (local linkage = 3.128), also cluster in very few occupations. From this program, 67 percent of students become *Medical and Pharmaceutical Technicians* (ISCO 321) another 10 percent work as *Personal Care Workers*. Among the vocational programs, the lowest occupational specificity is attached to the upper secondary (MBO-4) program *Commerce* with a specificity value of 0.645 and to the HBO short program in the same sector (0.769). For both programs, graduates work in many different occupations with no occupation receiving more than around 10 percent of the graduates

7.2. Occupational specificity over the life course

From the descriptive results it becomes clear that occupational specificity is not well captured by a vocational dichotomy. For the multivariate results we, therefore, investigate what the effects of having a (more) occupation-specific educational program are on employment. Following the vocational decline hypothesis, we investigate the returns over the life course, expecting that having an occupation-specific degree becomes a penalty in later life. Please note that in the tables the measure of occupational specificity is standardized to make the interactions easier to interpret. Furthermore, the age variable is recoded so that a value of zero is equal to the age of 16 and divided by 10 to make the coefficients better readable. In Table 3, we begin with presenting a model with age and occupational specificity and without interaction effect and add the interaction(s) in the subsequent model. Following the considerations about non-linear effects above, we present the model with age terms up to age quartic and the pertaining interactions as our main model (Models 3 and 4 for men and women). We compare this model to a simpler model that has been used in the literature most often (Models 1 and 2 for men and women).

Model 1 includes age, age squared and the occupational specificity measure next to a number of controls (educational level, region and survey year). Occupational specificity has a positive and significant effect for both men and women. This simple model indicates that a one standard deviation increase in occupational specificity increases the probability of being employed with 0.008 or 0.8 percentage points for men and 0.9 percentage points for women.

The first finding is thus that occupational specificity is positively associated with the probability to be employed for both men and women. Having graduated from a more occupationally specific educational program advances chances in the labor market. The influence of age takes a curvilinear pattern: The coefficient for age is positive and significant showing that an increase of age by one year leads to a ($34.5/10 =$) 3.45 percentage point increase in the probability of being employed for men and a 2.43 percentage point increase for women.[16] This increase is quite substantive. Interestingly, the increase for women is less strong indicating different career patterns for men and women. The squared term of age is negative and significant for both genders. This shows that even if the employment probability increases with age, this increase slows down and reverses eventually. The effect of level of education is consistently positive. Higher levels lead to a higher employment probability.

The predicted effects in Model 1 are the predicted effects for the whole workforce, aged 16 to 65. In Model 2, we investigate if the effect of occupational specificity changes over the life course by adding its interaction with age. For both men and women we see that there is a significant negative interaction, indicating that the effect of occupational specificity on employment decreases with age. For men, we see that the predicted effect for a one standard deviation increase in occupational specificity is 0.021, decreasing by $0.005/10$ for each year that they grow older. Similarly, for women we find that the predicted effect of occupational specificity for 16 year olds is 0.027, decreasing by $0.007/10$ for each year. First, this confirms existing work on the importance of occupational specificity for the transition from school to work. For a 16-year-old male, an increase of linkage by one standard deviation leads to a 2.1 percentage point higher probability of being employed, an effect that is not only significant but also substantial in size. For a female of the same age the effect is 2.7 percentage points. Having an occupationally specific degree pays off at the start of the career in finding

[16] We need to divide the coefficient by 10 here to retain the original meaning of the age variable that was divided by 10 for display in the table.

Table 3
Linear probability models for the life course with employment as dependent variable.

	Men				Women			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Occ. Specificity (standardized)	0.008 ***	0.021 ***	0.007 ***	−0.016	0.009 ***	0.027 ***	0.008 ***	−0.002
	(0.001)	(0.003)	(0.001)	(0.011)	(0.002)	(0.003)	(0.002)	(0.013)
Age/10 (Age 16 = Value 0)	0.345 ***	0.341 ***	0.796 ***	0.813 ***	0.243 ***	0.240 ***	0.341 ***	0.335 ***
	(0.005)	(0.005)	(0.024)	(0.027)	(0.005)	(0.005)	(0.026)	(0.031)
Age^2 /10	−0.077 ***	−0.076 ***	−0.568 ***	−0.580 ***	−0.061 ***	−0.061 ***	−0.296 ***	−0.295 ***
	(0.001)	(0.001)	(0.018)	(0.020)	(0.001)	(0.001)	(0.020)	(0.022)
Age^3 /10			0.172 ***	0.175 ***			0.103 ***	0.104 ***
			(0.005)	(0.006)			(0.006)	(0.006)
Age^4 /10			−0.019 ***	−0.019 ***			−0.013 ***	−0.013 ***
			(0.001)	(0.001)			(0.001)	(0.001)
Age/10 × Occ. Specificity		−0.005 ***		0.116 ***		−0.007 ***		0.114 ***
		(0.001)		(0.024)		(0.001)		(0.029)
Age^2 /10 × Occ. Specificity				−0.102 ***				−0.107 ***
				(0.018)				(0.021)
Age^3 /10 × Occ. Specificity				0.031 ***				0.034 ***
				(0.005)				(0.006)
Age^4 /10 × Occ. Specificity				−0.003 ***				−0.003 ***
				(0.001)				(0.001)
Educational level (ref = pre-primary)								
primary	0.115 ***	0.113 ***	0.116 ***	0.113 ***	0.175 ***	0.172 ***	0.174 ***	0.167 ***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.014)	(0.014)	(0.014)	(0.014)
lower secondary	0.219 ***	0.219 ***	0.219 ***	0.220 ***	0.291 ***	0.289 ***	0.288 ***	0.283 ***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.013)	(0.013)	(0.013)	(0.013)
upper secondary	0.275 ***	0.275 ***	0.277 ***	0.276 ***	0.439 ***	0.439 ***	0.438 ***	0.437 ***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.013)	(0.013)	(0.013)	(0.013)
post secondary	0.283 ***	0.283 ***	0.284 ***	0.283 ***	0.475 ***	0.476 ***	0.470 ***	0.472 ***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.015)	(0.015)	(0.015)	(0.015)
tertiary	0.318 ***	0.319 ***	0.321 ***	0.321 ***	0.517 ***	0.517 ***	0.523 ***	0.522 ***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.013)	(0.013)	(0.013)	(0.013)
doctorate	0.351 ***	0.354 ***	0.358 ***	0.361 ***	0.522 ***	0.518 ***	0.537 ***	0.532 ***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.024)	(0.024)	(0.024)	(0.024)
Constant	0.265 ***	0.270 ***	0.191 ***	0.184 ***	0.150 ***	0.154 ***	0.209 ***	0.214 ***
	(0.018)	(0.018)	(0.020)	(0.021)	(0.016)	(0.016)	(0.019)	(0.020)
Region fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
N	106,445	106,445	106,445	106,445	108,307	108,307	108,307	108,307
R^2	0.183	0.183	0.208	0.209	0.201	0.201	0.217	0.219
BIC	82345.479	82321.704	79033.506	78979.048	118134.168	118106.228	115911.956	115772.289

Note: Standard errors in parentheses. Sampling weights are applied.
Note: Age is divided by 10 for better readability of the coefficients.
Note: Occupational Specificity is standardized within genders to facilitate interpretation of the effects.
Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: EBB 2010–2012, own calculations.

employment. This is in line with the theoretical expectation that graduates with specific skills are attractive for employers as they will be immediately productive. Second, the negative interaction indicates that the premium associated with an occupationally specific degree decreases over the life course. However, while the interactions in Model 2 in Table 3 show that the positive effect of occupation-specific education decreases with age, it is hard to see how severe the decline is and whether occupational specificity becomes a real penalty - as we would expect from earlier research (Hanushek et al., 2017). To evaluate this question we will look at employment over the life course with predicted probabilities and marginal effects plots (Figs. 2 and 3).

Before we turn to these plots, we look at Model 3 and 4. Our analyses of non-linear effects and model fit showed that the more simple model used in previous research might not capture the employment patterns over the life course well. Therefore, Model 3 includes occupational specificity as well as age, age squared, age cubed, and age quartic. Model 4 additionally includes interactions of all these age terms with occupational specificity. All effects in these models besides the main effect for occupational specificity in Model 4 are significant. As the interpretation of coefficients with that many terms is very unintuitive, we will rely on predicted probabilities and marginal effects to interpret the two models. We look at two sets of graphs.

Fig. 2 shows predicted probabilities of being employed over the life course for three different levels of occupational specificity: low (10th percentile of the distribution), average (50th percentile) and high (90th percentile). Sub-figures a and c show the results of the simple decline model (Model 2 in Table 3) for men and women. Sub-figures b and d show the full model with all age terms and interactions (Model 4 in Table 3).

In the predicted probabilities graphs for the simple model, it can be seen that employment probabilities rise for all individuals up

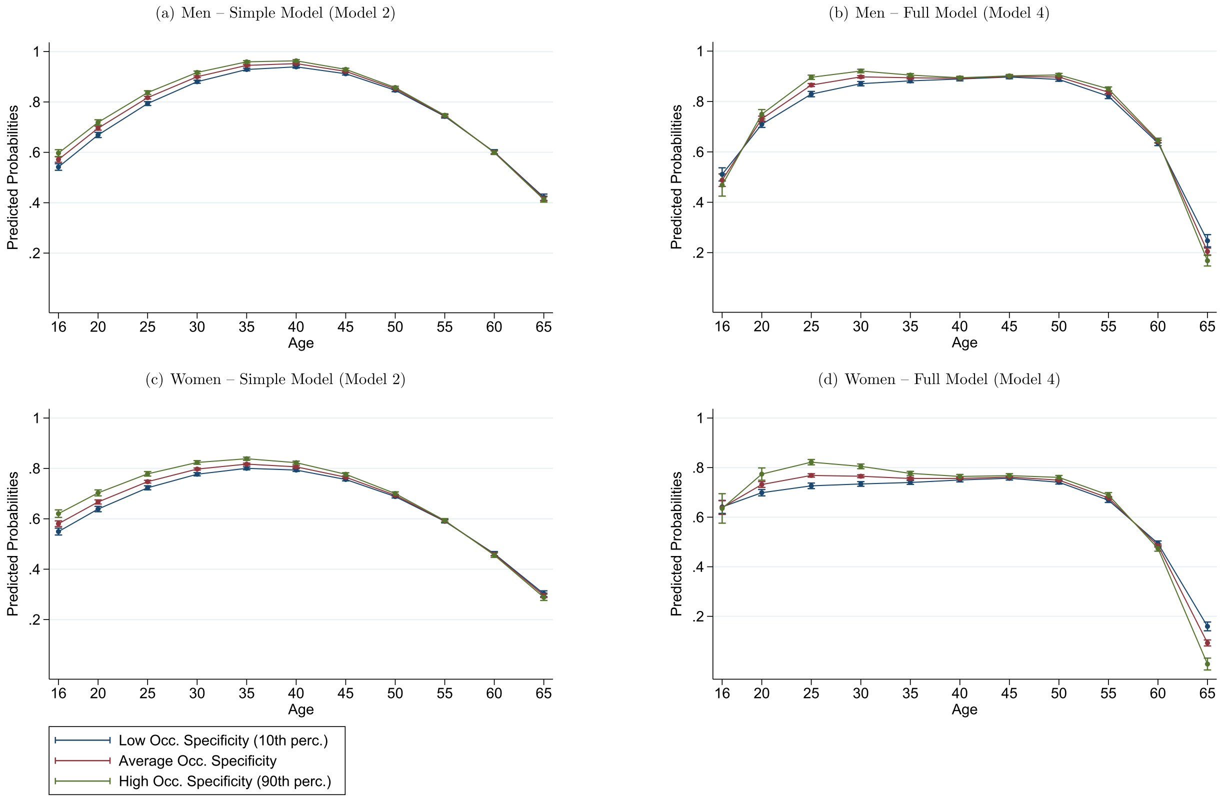

Fig. 2. Predicted probabilities of being employed for different levels of linkage strength over the life course (other variables at mean).

to the age of about 40 years for men and 35 years for women and then begin a decline. This curvilinear pattern of age with a peak in the mid thirties reflects the results of previous studies (e.g. Hanushek et al., 2017). More importantly, we see that having a high level of occupational specificity yields a visible advantage early in the career, but the effect diminishes over the life course. This advantage for individuals from highly occupation specific program remains substantial until about 30–35 years of age. It shows the strong benefit of vocationality in the transition from school to work. With increasing age, the benefit of occupational specificity decreases.

However, it can be seen that the predicted employment probabilities of graduates from highly specific programs (90th percentile) stay higher than for other individuals up to shortly before 60 years of age. This is a turning point much later in the career than predicted by Hanushek et al. (2017). The figure makes also clear that basically nowhere in the career those with a high level of occupational specificity are worse off. If anything, we see a convergence in the employment probabilities for workers from non-specific and specific programs towards the end of the career. Given the strong benefit of having a specific degree early in the career, the overall effect of having a specific degree is positive. The patterns for men and women are similar here, although employment probabilities for women are on average lower and start to decline much earlier in the life course than those of men.

The results from the more complex model, including multiple terms of age (sub-figures b and d), are more nuanced. At the very start of the career (age 16) we now see a slight negative effect of occupational specificity: those from programs with high occupational specificity seem to be worse off than those with low specificity. At the age of 20, this effect reverses and a high occupational specificity becomes an advantage compared to a low occupational specificity. Subsequently, high specificity stays beneficial up to an age of shortly below 60 years, although the effect is not strong anymore after the age of 40. At the end of the career we, again, see a convergence and finally a reversal of employment probabilities. Here, the conclusions from the complex models are slightly different to those from the simpler model: those with an occupation-specific degree are outperformed by those with a more general degree very late in the career (60–65 years). At this point, occupational specificity turns into a disadvantage.

For the very young male workers aged 16 to 20, we see a (non-significant) negative effect of occupational specificity. This effect is not surprising considering that a high share of individuals at this age are still in education and thus not part of our analysis. The set of youth that are already on the labor market at this age might be a rather negatively selected sample who stopped schooling very early. However, this result also shows that the claim of occupational specificity facilitating the school to work transition has to be carefully investigated especially for individuals at a very young age.

In general, the results from the complex model confirm the pattern found with the more simple model, even if there is a need for closer investigating the very young age group: Occupational specificity is positive for employment in the early career and has no effect or a slightly negative effect at the end of the career. This negative effect, however, only shows at the very end of the career at an age of above 60 years and cannot outweigh the advantages of occupational specificity at earlier stages of the career.

Fig. 3 shows the change in the marginal effect of occupational specificity even more clearly. Again, sub-figures a and c show the

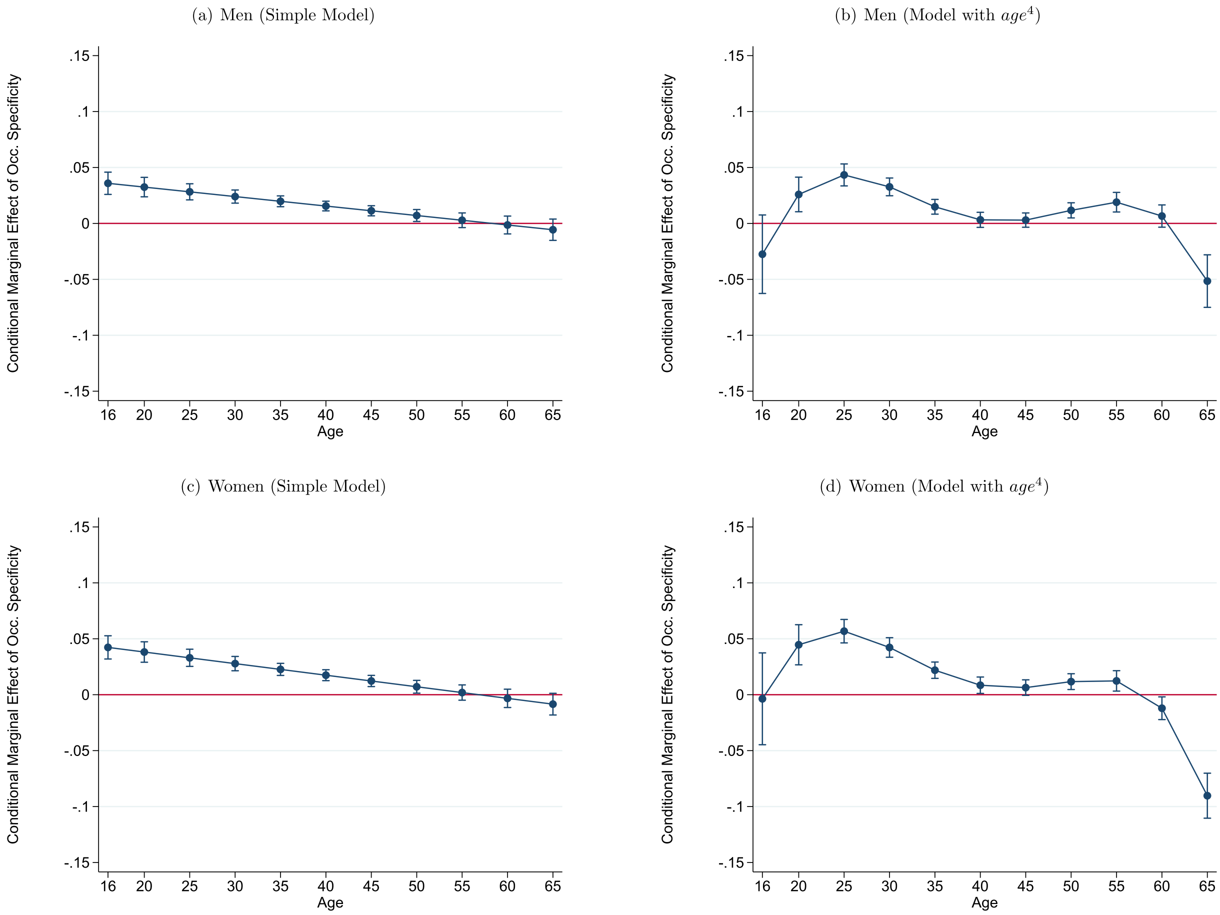

Fig. 3. Conditional marginal effects of linkage strength at different ages.

simple model and sub-figures b and d depict the more complex model. In the simple model, the effect of occupational specificity is strong and significant for younger ages but decreases over age and finally reaches zero at an age between 55 and 60. This point of reversion is very similar for men and women. After the age of 60 the effect of linkage strength becomes slightly negative but does not reach statistical significance. During the largest part of their career, graduates from highly vocational programs benefit from their training. The results from the conventional model, therefore, do not indicate that there is a vocational decline in the sense that having an occupationally specific degree becomes a real penalty for a substantial part of the career.

Sub-figures b and d, show the patterns for the more complex model. Again, the effect of occupational specificity is significantly positive for a large part of the career, between 20 and 35 years and again between 45 and 60 years of age. In the forties, the effect of occupational specificity seems to be insignificant. This could be due to the fact that now also the career of those who finished education late finally takes off. The important result in this figure, however, is that only at the very last point of the career at 60 (for women) or 65 years (for men), occupational specificity turns into a disadvantage. This disadvantage does not outweight the benefits from occupational specificity earlier in the career. In this more complex model, we again see that at a very young age of 16, occupational specificity has a non-significant negative effect. The large standard error, however, shows that the prediction of this effect is not very precise, due to the fact that the sample for this age group is rather small.

8. Discussion

Recent studies focus on the life course effects of vocational education on employment, arguing that there is a *vocational decline*: while having occupation-specific skills is a benefit at the start of the career, it becomes a penalty for older workers (Hanushek et al., 2017; Forster et al., 2016). Occupation-specific skills lead to a great start, because graduates who have a lot of them will be attractive for employers seeking workers that are immediately productive. However, with technological innovations, occupation-specific skills that were relevant when entering the labor market become obsolete later in the career, leading to worse employment prospects for older workers with occupation-specific skills. Using Labor Force Survey data, in this article we analyzed employment effects of occupational specificity for the Netherlands. We have two major findings.

First, in this article we argue that the common dichotomous conceptualization of vocational education is inaccurate. The vast majority of research into the labor market effects of vocational education (e.g., Shavit and Müller, 1998; Hanushek et al., 2017; Forster et al., 2016) uses a two-category indicator for the denomination of an educational program: either it is general or it is vocational. An often explicit assumption is that the group of vocational programs provides occupation-specific skills, whereas this is not the case for educational programs labeled as general. In this article we use a new measure for occupational specificity that measures the extent to which graduates from the same educational program (defined by level and field) cluster in the same (set of) occupation(s). We show that the dichotomous distinction does not do justice to the much more gradual differences in occupational specificity. On average, there is hardly a difference in the occupational specificity of programs labeled as general and programs labeled as vocational. Moreover, differences within these categories are far bigger than differences between them.

Second, our multivariate results show that graduates from more occupational specific programs are much more likely to be employed in their early career than workers from less specific programs. In line with the vocational decline hypothesis, this benefit decreases over their life course. However, while the premium associated with occupational specificity decreases, it only becomes a disadvantage very late in the career. Only for workers that are older than 60, our models predict a benefit for those who received a more general education. The penalty itself is small and only occurs much later than what earlier studies have found (Hanushek et al., 2017). For very young workers (until 20 years of age), we find a non-significant negative effect of occupational specificity. The observed patterns are very similar for men and women.

These findings have several implications for existing literature. The individual level benefits of occupational specificity that are found for the early labor market career confirm earlier studies on the topic (Shavit and Müller, 1998; Breen, 2005; Scherer, 2005). In the Netherlands, occupational specificity is an important positive predictor for the likelihood to be employed at an age of 20–55. However, the literature on the school-to-work transition should re-evaluate the precise process of the transition to the labor market and the timing of these positive effects, given that we find null effects for very young individuals. It might be that the null effects for this age group might have to do with the negatively selected sample of individuals that are already in the labor market at such young ages but this has to be investigated further.

Our results also show that we should think about occupational specificity not as something that is about different school types, but instead focus on specific educational programs, defined both by level *and* field. In line with recent work (DiPrete et al., 2017), we show that it is important to look at the granular level of education to understand its returns in the labor market.

The convergence of life course employment probabilities in the Netherlands with only a small disadvantage for vocational workers at the end of the career does not confirm previous research that would have predicted a larger penalty for those with an occupation-specific degree (Hanushek et al., 2017). There might be several reasons for this missing penalty that should be investigated by further studies. On-the-job training might effectively prevent the decline of skills in the Netherlands. It might also simply be the case that the proposed mechanism is incorrect: workers that were trained in educational programs that vary in their occupational specificity do not have to adjust differently to technological change. However, recent legislation about moving the retirement age up to 67 or even older, make the small disadvantages at the very end of the career worthwhile to study more closely. If the penalty increases after 65 this may become a more serious issue the more workers still remain in the workforce at this age.

These findings are also relevant for policy focused on vocational education. In the Netherlands, occupation-specific training increases the employability of young people. By fostering a high vocationality in educational programs, graduates benefit in the beginning of their career without facing substantial disadvantages later. This finding also shows that the vocational content of programs within educational levels is important when looking for ways to optimize the employability of graduates. This advice should be especially considered in debates that seek to focus policy on increasing the educational level of all graduates instead of reforming the content of programs within levels. As the heterogeneity of occupational specificity within programs that are classified as vocational or general is high, it will be vital to look beyond those broad categories when trying to improve occupational specificity of education.

There are of course several aspects of our study that should be improved in future work. First, although we control for all relevant observables that are available in the data, there are factors that are missing but would ideally be taken into account. For example, we cannot control for the skill levels and socio-demographic background of respondents, two factors that potentially affect both the selection into a specific form of education and the labor market outcomes of respondents. While Forster et al. (2016) show that both including skills and socio-economic background do not take away much of the effect of vocational education, this is something that needs to be investigated more closely. Second, just like Hanushek et al. (2017), with our cross-sectional models we are not able to disentangle an age effect (as individuals grow older, the effect of occupational specificity decreases) from a cohort effect (with technological change, the effect of occupational specificity decreases). We discuss this in more detail in Appendix C. Furthermore, as we only observe snapshots of labour market careers, we cannot observe adult training patterns for individuals in different occupations directly. Future research should try to look at these issues in more detail.

Acknowledgement

The research in this article has been supported by a Veni grant from the Netherlands' Organization for Scientific Research (451-15-001). Previous versions of this article were presented at the DFG summer school on labor market research at the ZEW Mannheim (Germany) and at the ROA conference on human capital over the life-cycle in Maastricht (the Netherlands). We thank participants and the reviewers of Social Science Research for their helpful suggestions.

Appendix A. The educational system in the Netherlands

An overview of the Dutch educational system is presented in Fig. A1. The figure shows the different school types and in parentheses the respective level in the Dutch educational classification (SOI). The full names of the Dutch school types are presented in Table A1. From age 0 to 4, children attend different form of pre-primary institutions. At an age of four years they enter primary school (*basisschool*) of which the first two grades are still considered as pre-primary education on SOI-level 10. The remaining six years of basisschool are subsumed under level 20 (primary education).

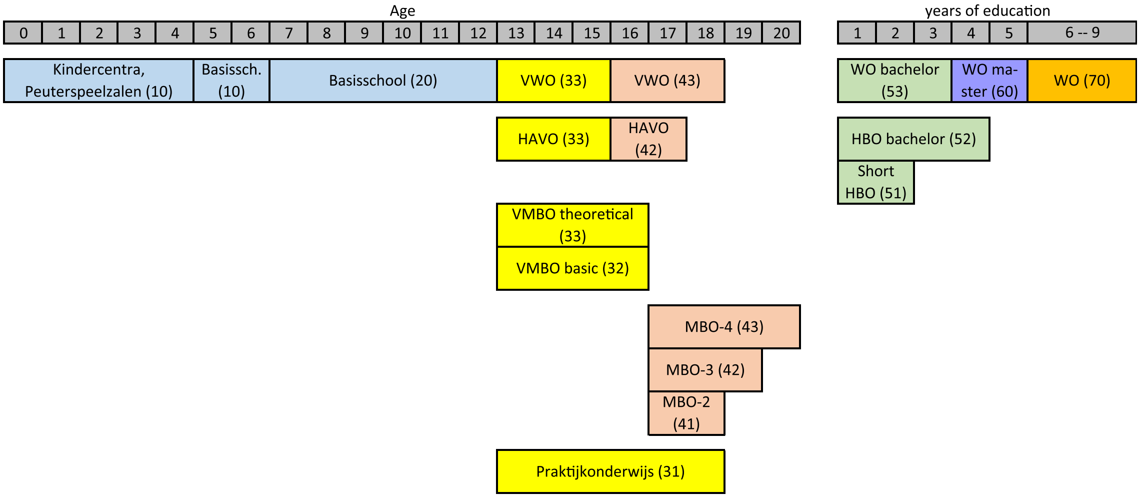

Fig. A1. Educational System of the Netherlands.
Note: The numbers in parentheses are the level as used in SOI and in the level-field code in this paper.

From an age of twelve, the Dutch educational systems is differentiated in several tracks. In the first three to four years of the tracked system, VWO, HAVO and the theoretical track of VMBO are considered as *lower secondary education, high level* (33). The more basic VMBO tracks are considered as *lower secondary intermediate* (32) in the SOI classification. Vocational courses which are termed *Praktijkonderwijs* as well as MBO 1 programs are considered as *low level lower secondary education* (31).

In upper secondary education, the last three years of VWO as well as MBO level 4 programs (middle-management training) are considered as high level (43), the two final years of HAVO and MBO level 3 programs (professional training) are categorized as intermediate (42), and MBO level 2 programs (basic vocational training) are seen as low level (41). While VWO and HAVO are considered as general education, the different MBO programs are classified as vocational in the dichotomous measure of vocationality.

In higher education it is distinguished between scientific WO bachelor programs (53) and professional HBO programs (51 and 52). The master (60) and doctorate levels (70) are not differentiated in different sub-levels.

Table A1
School types in the Dutch educational system.

Abbreviation	Full name	Translation
VMBO	Voorbereidend middelbaar beroepsonderwijs	Preparatory intermediate vocational education
HAVO	Hoger algemeen voortgezet onderwijs	Higher general continued education
VWO	Voorbereidend wetenschappelijk onderwijs	Preparatory academic education
MBO	Middelbaar beroepsonderwijs	Intermediate vocational education
HBO	Hoger beroepsonderwijs	Higher vocational education
WO	Wetenschappelijk onderwijs	Academic Education, University

Appendix B. List of educational and occupational categories used in the analyses

Table B1 shows all combinations of educational levels and fields that exist in our data with their respective linkage strength. In total, our data contains 138 level-field combinations. Table B2 shows an overview of all ISCO 3-digit categories that are present in our sample.

Table B1
Existing level-field combinations and their linkage strength.

Fields of Education (SOI classification)		Levels of Education (SOI-classification)												
		10	20	31	32	33	41	42	43	51	52	53	60	70
01	General education	1.356	0.776			0.49		0.39	0.45					
10	Teachers										1.55		2.335	
11	Teachers general education								1.443		2.498			
12	Teachers humanities, social sciences, communication and arts										1.946			
14	Teachers technical subjects and transport										1.227			
16	Teachers (health) care, sports and other								1.516		1.44			
20	Humanities, social sciences, communication and arts											0.631		
21	Languages												1.17	
22												1.332		
23	Social sciences										0.999		1.161	
24	Communication, media, information										1.228		1.454	
25	Arts, expression								1.379		1.365		1.583	
27	Humanities, social sciences, communication and arts with differentiation								1.402		1.629			
30	Economics, commercial, management and administration				0.954				0.806	0.793		1.077	1.908	
31	Economics										1.392		1.327	
32	Commercial					0.935	1.348	0.83	0.645		0.769		0.713	
33	Management										0.804		1.034	1.38
34	Human resource management, personnel										1.499			
35	Administration, secretarial					0.835	1.063	1.067	1.124		1.933			2.611
37	Economics, commercial, management and administration with differentiation										0.928		1.267	
40								1.089		2.36				
41	Law, public administration										1.067		1.802	3.067
42	Public order, safety						2.278	3.118						
51	Mathematics, natural sciences										2.126		1.57	1.848
52	Computer science						1.754		2.006		2.32		2.015	
60	Engineering					1.029	2.902	1.474	1.267		0.961		2.419	
61	Engineering general								1.713				1.772	
62	Electrical engineering					1.357			2.029		1.721			
63	Construction				1.812	1.505	2.24	1.995	1.53		1.755		1.689	
64	Metal processing, vehicle and tool manufacturing				1.833	1.413	1.843	1.989	1.457		1.392		1.937	
65	Process technology						2.296						1.912	
66	Textile and leather processing, other												1.373	
67	Engineering with differentiation										1.253			
70	Agriculture and environment												1.687	
71	Agriculture					1.04	1.716	1.875	1.74		1.205			

77	Agriculture and environment with differentiation								1.363			
81	Health care					2.416	2.147		2.171		1.976	3.441
82	Care, community services		1.131	0.878	1.418	1.511	1.146		1.003		1.187	
87	Health care and community services with differentiation						3.128		1.92		1.512	
90	Hotels, gastronomy, tourism, leisure, transport and logistics			1.059	2.149	2.031		2.071				
91	Hotels, gastronomy, tourism and leisure				1.523	2.164	0.924		0.858			
92	Transport and logistics			2.412			1.824		1.029			
97	Hotels, gastronomy, tourism, leisure, transport and logistics with differentiation								0.789			
98	Other	1.371	1.013	1.31	1.174	0.768	1.203	1.276	1.031	0.69	1.558	1.319

Table B2
List of 3-digit ISCO categories.

110 Chief executives, senior officials and legislators	111 Legislators and senior officials	112 Managing directors and chief executives	121 Business services and administration managers	122 Sales, marketing and development managers	131 Production managers in agriculture, forestry and fisheries	132 Manufacturing, mining, construction, and distribution managers
133 Information and communications technology service managers	134 Professional services managers	141 Hotel and restaurant managers	142 Retail and wholesale trade managers	143 Other services managers	210 Science and engineering professionals	211 Physical and earth science professionals
212 Mathematicians, actuaries and statisticians	213 Life science professionals	214 Engineering professionals (excluding electrotechnology)	215 Electrotechnology engineers	216 Architects, planners, surveyors and designers	221 Medical doctors	222 Nursing and midwifery professionals
223 Traditional and complementary medicine professionals	225 Veterinarians	226 Other health professionals	230 Teaching professionals	231 University and higher education teachers	232 Vocational education teachers	233 Secondary education teachers
234 Primary school and early childhood teachers	235 Other teaching professionals	241 Finance professionals	242 Administration professionals	243 Sales, marketing and public relations professionals	250 Information and communications technology professionals	251 Software and applications developers and analysts
252 Database and network professionals	261 Legal professionals	262 Librarians, archivists and curators	263 Social and religious professionals	264 Authors, journalists and linguists	265 Creative and performing artists	310 Science and engineering associate professionals
311 Physical and engineering science technicians	312 Mining, manufacturing and construction supervisors	313 Process control technicians	314 Life science technicians and related associate professionals	315 Ship and aircraft controllers and technicians	320 Health associate professionals	321 Medical and pharmaceutical technicians
322 Nursing and midwifery associate professionals	324 Veterinary technicians and assistants	325 Other health associate professionals	331 Financial and mathematical associate professionals	332 Sales and purchasing agents and brokers	333 Business services agents	334 Administrative and specialized secretaries
335 Regulatory government associate professionals	341 Legal, social and religious associate professionals	342 Sports and fitness workers	343 Artistic, cultural and culinary associate professionals	350 Information and communications technicians	351 Information and communications technology operations and user support technicians	352 Telecommunications and broadcasting technicians

411 General office clerks	412 Secretaries (general)	413 Keyboard operators	421 Tellers, money collectors and related clerks	422 Client information workers	431 Numerical clerks	432 Material-recording and transport clerks
441 Other clerical support workers	511 Travel attendants, conductors and guides	512 Cooks	513 Waiters and bartenders	514 Hairdressers, beauticians and related workers	515 Building and housekeeping supervisors	516 Other personal services workers
520 Sales workers	521 Street and market salespersons	522 Shop salespersons	523 Cashiers and ticket clerks	524 Other sales workers	531 Child care workers and teachers' aides	532 Personal care workers in health services
541 Protective services workers	611 Market gardeners and crop growers	612 Animal producers	613 Mixed crop and animal producers	621 Forestry and related workers	622 Fishery workers, hunters and trappers	711 Building frame and related trades workers
712 Building finishers and related trades workers	713 Painters, building structure cleaners and related trades workers	721 Sheet and structural metal workers, moulders and welders, and related workers	722 Blacksmiths, toolmakers and related trades workers	723 Machinery mechanics and repairers	731 Handicraft workers	732 Printing trades workers
741 Electrical equipment installers and repairers	742 Electronics and telecommunications installers and repairers	750 Food processing, wood working, garment and other craft and related trades workers	751 Food processing and related trades workers	752 Wood treaters, cabinet-makers and related trades workers	753 Garment and related trades workers	754 Other craft and related workers
811 Mining and mineral processing plant operators	812 Metal processing and finishing plant operators	813 Chemical and photographic products plant and machine operators	814 Rubber, plastic and paper products machine operators	815 Textile, fur and leather products machine operators	816 Food and related products machine operators	817 Wood processing and papermaking plant operators
818 Other stationary plant and machine operators	821 Assemblers	831 Locomotive engine drivers and related workers	832 Car, van and motorcycle drivers	833 Heavy truck and bus drivers	834 Mobile plant operators	835 Ships' deck crews and related workers
911 Domestic, hotel and office cleaners and helpers	912 Vehicle, window, laundry and other hand cleaning workers	921 Agricultural, forestry and fishery labourers	931 Mining and construction labourers	932 Manufacturing labourers	933 Transport and storage labourers	941 Food preparation assistants
961 Refuse workers	962 Other elementary workers					

Appendix C. Cohort changes in linkage strength

One concern with using the linkage measure in our analysis is that we assume that linkage strength does not change over cohorts. Given the cross-sectional data that we use, we need to make this assumption in order to investigate the effects of occupational specificity across the whole labor market career using respondents of different age in our sample. To address this strong assumption, where we calculate the local linkage scores for all fields and levels separately for different subgroups or cohorts in our data: 16–35 year olds, 36–50 year olds, and 51–65 year olds. This analysis indicates whether linkage strength for the same educational category changed over time, and if it did so in a systematic way. We only know workers current occupation which means that we still have to assume that labor markets are inflexible and that workers stayed in the occupation that they entered after completing school. Nevertheless, these analyses give some indication of how local linkage has changed across cohorts in our data.

Table C1
Correlation of linkage strength between cohorts.

	15–35 year olds	36–50 year olds	51–65 year olds
15–35 year olds	1.00		
36–50 year olds	0.86	1.00	
51–65 year olds	0.80	0.85	1.00

Table C1 shows that, on average, the measures of linkage strength correlate quite strongly across the three cohorts. All correlations between pairs of cohorts are 0.80 or higher. However, this correlation could still be strong if there is a direction in how linkage differs across cohorts. If linkage is stronger for more recent cohorts (i.e., 15–35 year olds) than older cohorts (i.e., 51–65 year olds), this is an important factor to take into account in our discussion. In other words: even with a high correlation, linkage could still have systematically decreased over cohorts, for example because linkage was stronger 50 years ago than now. DiPrete et al. (2017) take a similar step, in calculating the linkage strength for younger workers only, finding higher linkage. Their ratios indicate that the linkage is generally higher for more recent cohorts (DiPrete et al., 2017:1905).

Table C2
Ratios and differences.

	Difference	Ratio
15–35 vs. 36–50	0.23	1.21
36–50 vs. 51–65	−0.01	0.99
15–35 vs. 51–65	0.24	1.21

For our analyses we find that among the 181 level and field combinations under study, the same holds true. Local linkage is – on average – stronger for the most recent cohort. Table C2 shows that the absolute difference is 0.23 or relatively 20 percent higher. However, there is no difference between the middle and old cohort with an absolute difference of −0.01 and a ratio of 0.99. As a consequence the difference between the youngest and oldest cohort is similar to that of the difference between the youngest and middle cohort. This does not mean that there is no change in local linkage for all fields: Fig. C1 shows that there is substantial variation in how linkage has changed.

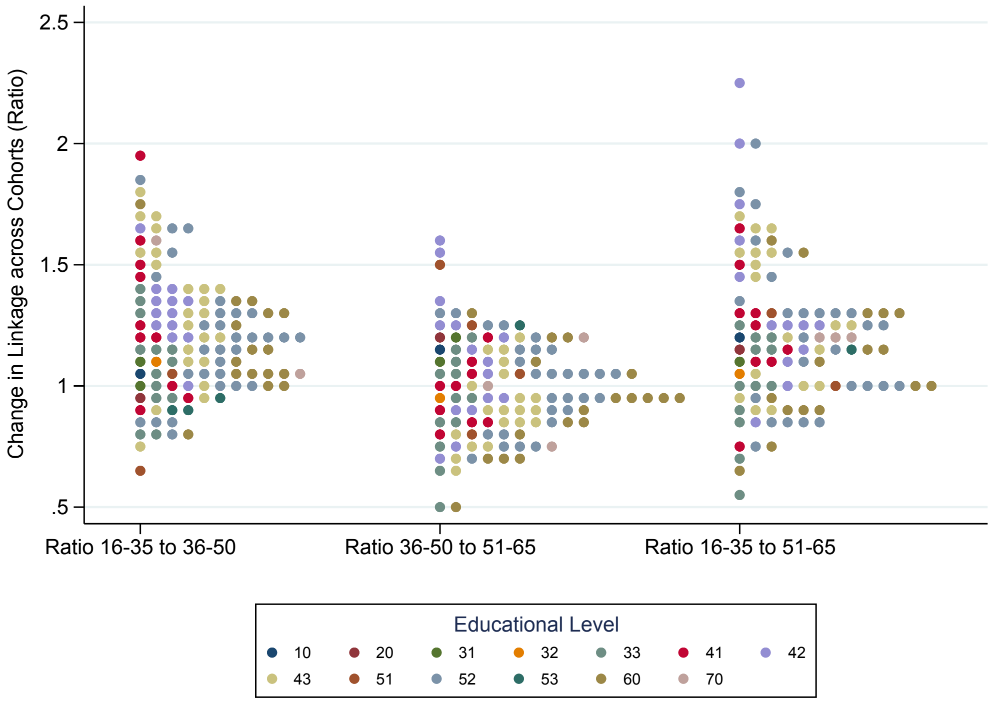

Fig. C1. Linkage changes across cohorts – single educational categories.

The first column of dots shows the ratio between the linkage strength of a category for the young cohort (16–35) and the middle aged cohort (36–50). The other two columns show the ratios between the middle and the old and between the young and the old cohort. The y-axis shows the relative change in linkage between the two cohorts (ratio between the two linkage scores). The colors symbolize the different educational levels as displayed in the legend. For readability, the dots are stacked horizontally if their values for the ratio are within a 0.05 range. A ratio of 1 means that the linkage strength for this level-field did not change between the two respective cohorts. A ratio above 1 indicates that linkage strength got smaller and a ratio below 1 shows an increase in linkage from the former to the latter cohort.

For the change between the young and the middle aged cohort (column 1), we can see that most linkage scores declined (ratio above 1). For most level-fields linkage became lower. Between the middle cohort and the old cohort (column 2), the changes are more balanced around 1, some linkage scores decreased and others increased. Overall, the changes are smaller here and do not exceed more than 50 percent of the previous value. For the overall change between the young and the old cohort (column 3), we see more decrease than increase again. This change is mostly due to the changes between the young and the middle cohort. Looking at the different educational levels, we do not see a distinct pattern. While some fields within a level increase their linkage between the cohorts, other fields decrease. This figure again shows, that there is more change in linkage strength between the young and the middle aged cohort but little change between the middle aged and the old cohort. Overall the change seems to be not systematic related to some fields or levels, or to be ever-increasing between cohorts.

Of course these analyses are unable to really address the age-cohort issue, but they give some indications. Given that we see a lot of change between the recent and the middle aged cohort but not much change between the middle aged and the oldest cohort, we believe that the change in linkage strength portrays mostly an age effect and less a cohort effect. If cyclical effects in the labor market played a major role, or older cohorts had lower linkage because of peculiarities in the Dutch education system, we would expect to see a more pronounced change also between the middle and the old cohort.

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