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Maastricht University

Author information:

Sofie Cabus	Top Institute for Evidence Based Education Research (TIER), Maastricht University, (s.cabus@maastrichtuniversity.nl)
Ilja Cornelisz	Faculty of Behavioral and Movement Sciences at VU University Amsterdam (i.cornelisz@vu.nl)
Wim Groot	Top Institute for Evidence Based Education Research (TIER), Maastricht University en Universiteit van Amsterdam, (wim.groot@maastrichtuniversity.nl)
Carla Haelermans	Top Institute for Evidence Based Education Research (TIER), Maastricht University, (carla.haelermans@maastrichtuniversity.nl)
Chris van Klaveren	Faculty of Behavioral and Movement Sciences at VU University Amsterdam (c.p.b.j.van.klaveren@vu.nl)
Henriëtte Maassen van den Brink	Top Institute for Evidence Based Education Research (TIER), Universiteit van Amsterdam (h.maassenvandenbrink@uva.nl)
Deni Mazrekaj	Katholieke Universiteit Leuven (KU Leuven), Leuven Economics of Education Research (LEER), (deni.mazrekaj@kuleuven.be)
Melline Somers	Top Institute for Evidence Based Education Research (TIER), Maastricht University, (melline.somers@maastrichtuniversity.nl)
Florian Tomini	Top Institute for Evidence Based Education Research (TIER), Universiteit van Amsterdam (florian.tomini@maastrichtuniversity.nl)
Inne Vandyck	Top Institute for Evidence Based Education Research (TIER), Maastricht University, (i.vandyck@maastrichtuniversity.nl)

Inhoudsopgave

Thema 1: Verkenning en karakterisering van mismatch

Thema 2: Effectieve interventies om mismatch tegen te gaan

Thema 3: Verbetering aansluiting onderwijs en arbeidsmarkt

Horizontal Mismatch between Employment and Field of Education: Evidence from a Systematic Literature Review

Melline Somers; Sofie Cabus; Wim groot; Henriëtte Maassen van den Brink

Abstract

This paper provides a systematic review of the growing literature on the poor match between employees' field degree and the job requirements, also referred to as horizontal mismatch. We identify the different definitions used in the literature and find that each measure of horizontal mismatch yields substantially different incidence rates. We discuss the validity of the different measures and conclude that a more uniform definition of horizontal mismatch is needed. The likelihood of horizontal mismatch is among other things determined by the extent to which employees possess general skills as opposed to occupation-specific skills, and, it appears to be more frequently present among older workers. Compared to well-matched employees, horizontally mismatched workers generally incur a wage penalty, are less satisfied with their jobs, and are more likely to regret their study programme. The ensuing findings offer guidance to prevent horizontal mismatch as well as a roadmap for future research.

Keywords*:* education; labour; mismatch; occupation; skills

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1. Introduction

A good match between labour supply and labour demand is indispensable for graduates and companies and, consequently, for the economy as a whole. A mismatch between the attended field of education and the job, also referred to as horizontal mismatch (Robst, 2007a), can have serious consequences, not only for the individual because of unemployment risks (http://ec.europa.eu/social); wage penalties (Bender et al., 2013); or job dissatisfaction (Bender & Roche, 2013); but also for society. Education is an expensive investment and the highest return for society is obtained when individuals are well-matched to employers (Groot & Maassen van den Brink, 2000; Levin, Belfield, Muennig & Rouse, 2007; Levin & Rouse, 2012), such that the knowledge and skills that are acquired through education are optimally utilized on the labour market. Employees who are not able to fully utilize what they have learned through their field of education can suffer from wage penalties which, in turn, reduce the return to public investments in education (Robst, 2007a; Zhu, 2014). From an economic point of view, job-education mismatches are undesirable as it can result in foregone returns to public investments in education, but also in higher unemployment benefits and reduced tax revenues.

Job-education mismatches are usually measured by comparing graduates' educational attainment with the requirements for the job which can be expressed in terms of the level as well as the field of education. Workers who have attained a higher (lower) level of schooling than required are considered to be over-educated (under-educated). This type of mismatch is also referred to as vertical mismatch (Heijke, Meng & Ris, 2003). The incidence, determinants, and consequences of vertical mismatch have been well-documented (see e.g., Chevalier, 2003; Dolton & Silles, 2008; Dolton & Vignoles, 2000; Duncan & Hoffman, 1981a; Groeneveld & Hartog, 2004; Kiker, Santos & de Oliveira, 1997; McGuinness & Bennett, 2007; Verdugo & Verdugo, 1989; Verhaest & Omey, 2006), and various studies have provided useful summaries of this stream of literature by means of reviews as well as meta-analyses (e.g., Groot & Maassen van den Brink, 2000; Hartog, 2000; McGuinness, 2006; Rubb, 2003; Sloane, 2003). Research has confirmed that over-education is often associated with adverse outcomes for the employee such as wage penalties and job dissatisfaction (Groot & Maassen van den Brink, 2000; McGuinness & Sloane, 2011).

As noted earlier, employees are not solely matched based on their level of education, but also on the attended type or field of education (Robst, 2007a). Given that particular fields of education aim to prepare students for a range of occupations, matching job requirements with employees' field-specific

skills is essential for an efficiently functioning labour market. Moreover, students are assumed to make their schooling choices based upon educational preferences and with the expectation of finding future employment in field-related occupations (Betts, 1996; Holland, 1985). Holding a job that does not directly relate to the attended field of education can be considered undesirable in the case that graduates are not allowed to fully utilize the knowledge and skills that are acquired through formal education.

Considering the potential economic losses associated with an underutilization of skills, from a human capital theory perspective, horizontal mismatch is an undesirable phenomenon. Given that a proper allocation of skills on the labour market is in the best interest of society, an important question to be raised is how prevalent horizontal mismatch is and under what circumstances welfare losses are generated. We address these questions through four sub questions: (a) How is horizontal mismatch defined and measured? (b) To what extent is horizontal mismatch observed? (c) What are the determinants of horizontal mismatch? And (d) What are the consequences of horizontal mismatch? We answer these questions by means of a systematic review of the literature on mismatch between employees' job and the attended field of education. The objective of this paper is to present an integrated summary of the existing body of knowledge of horizontal mismatch. We identify where the conclusions of previous research converge and diverge and set the agenda for future research.

This paper proceeds as follows. Section 2 describes the literature search strategy. In Section 3 we address how horizontal mismatch has been defined and measured in the literature and what the advantages and drawbacks are of these definitions. Section 4 discusses the incidence of horizontal mismatch and Section 5 addresses the determinants of horizontal mismatch. In Section 6 we discuss the consequences of a mismatch between the attended field of education and employees' job. Finally, Section 7 discusses the main conclusions of this study and provides suggestions for future research.

2. Method

For our review, we set a series of inclusion criteria to narrow the extensive body of research down to a manageable set of studies for a thorough analysis: (a) The study is published between 1995 and 2015 in peer-reviewed academic journals in the Dutch or English language. (b) Empirical studies (descriptive, correlational, and experimental) are included, whereas theoretical, conceptual, and case studies are excluded. (c) The study deals with a mismatch between employees' job and the attended field of

education. Studies that focus on other types of mismatch (e.g. over- and under-education) were not retained.

We limit our literature search to the time window 1995–2015 as concerns about horizontal mismatch were first raised in 1995 by Witte and Kalleberg. Our systematic review is restricted to publications in the Dutch or English language due to a lack of resources and facilities for translation. We acknowledge that this restriction potentially introduces language bias as studies in non-English speaking countries are more likely to be published in an international English-language journal when significant results are found (Egger et al., 1997; Moher et al., 1996). However, the problem of language bias has reduced in the recent years due to a shift toward publications in the English language (Galandi, Schwarzer & Antes, 2006).[1] Furthermore, we only consider empirical articles published in academic journals and exclude qualitative research methods based on interviews, case studies, or conceptual work. This provides us with a better comparable body of research which improves the quality of our systematic literature review. Qualitative research, such as case studies, however, can provide useful insights if one wants to learn more about the precise discrepancies between graduates' attributes and employers' needs in a specific sector (see e.g., Nair, Patil & Mertova, 2009). Finally, given that we explore whether horizontal mismatch contributes to an inefficient allocation of skills on the labour market, we restrict our search to studies focusing on horizontal mismatch. Therefore, we exclude studies that concentrate on other types of mismatch such as under-education and over-education, as these do not answer our main research question and have already been well-documented in other reviews (e.g., Groot & Maassen van den Brink, 2000; Hartog, 2000).

We performed a computerized systematic search using a wide range of search terms or keywords, namely, "fit", "match", or "mismatch", combined with "college", "education", "major", "program", "programme", or "study", and "employment", "job", "labor", "labour", "occupation", or "work", and "field" (see Appendix 2. for the exact combination of search terms). The search was conducted in the following electronic databases: ERIC, EconLit, and SocINDEX. ERIC is used as the main search engine as it is the largest education database worldwide. EconLit and SocINDEX were used in order to add potentially missing articles to our search results. Figure 1 provides an overview of the selection process of relevant studies.

[1] As can be seen in Appendix 1, the majority of the records we consider for our review have been published after 2000 and we therefore consider the problem of language bias to be minimal.

ERIC initially provides 424 studies that were published between January 1995 and December 2015, whereas EconLit and SocINDEX provide us with 99 and 237 potential records, respectively. Excluding the duplicated, non-peer-reviewed, non-English, and non-Dutch records leaves us with 378 studies. Consequently, the studies were sorted based on the title and abstract which further allowed us to exclude 354 studies that did not meet our inclusion criteria. Reading the articles' full text, we keep 24 relevant papers.

The papers meeting the inclusion criteria were coded along a variety of dimensions. First, we recorded how horizontal mismatch was being measured and which variables were included in the analyses as explanatory or outcome variable. The data that were extracted also included the year of publication, the number of countries included, the type of data, the year of data collection, the research method, and the sample size. The first author performed the search and each included article was read and coded independently by all authors. Discrepancies between the obtained results were discussed until agreement was reached among the authors. We did not undertake a formal quality analysis due to the methodological diversity of the retrieved articles. Instead, we included a qualitative discussion of method issues when it was considered relevant.

Table 1 presents the selected studies and provides an overview of the data that were extracted. Most studies included in our review are correlational and make use of cross-sectional data, whereas no experimental studies were found. The nature of correlational studies is subject to several limitations. Outcomes that are associated with horizontal mismatch are not necessarily caused by the acquired field degree as students select themselves into fields. Moreover, the skills and knowledge that workers possess vary across graduates with the same educational background, but are often unobserved. Nonetheless, correlational studies can still be informative provided that field degrees still capture a substantial part of the skills that graduates have acquired through formal education.

Figure 1: Selection process

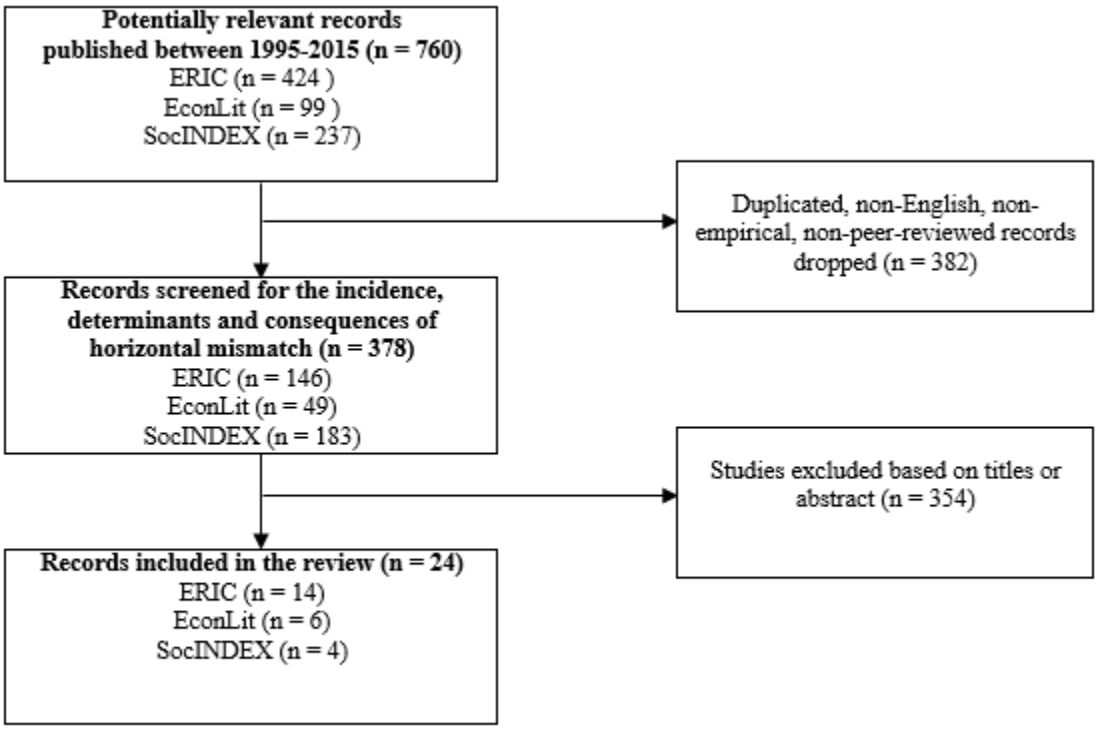

Table 1: General Description of Publications Included in the Analysis (24 publications reviewed)

Classification category	Sub-categories	N	Reference index in Appendix 1
Year of publication	1995-2000	1	1
	2001-2005	3	2, 3, 4
	2006-2010	8	5, 6, 7, 8, 9, 10, 11, 12
	2011-2015	12	13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24
Number of countries included in the study[a]	Single country	18	1, 2, 3, 5, 6, 7, 8, 10, 11, 12, 13, 14, 15, 17, 18, 19, 23, 24
	Several countries	6	4, 9, 16, 20, 21, 22
Type of data	Cross sectional data	18	1, 2, 4, 5, 6, 9, 10, 11, 13, 16, 17, 18, 19, 20, 21, 22, 23, 24
	Time series data	4	3, 7, 8, 15
	Panel data	2	12, 14
Year of data collection	1980-1985	2	1, 12
	1986-1990	4	1, 9, 12, 16
	1991-1995	5	3, 5, 6, 12, 14
	1996-2000	5	2, 4, 7, 10, 14
	2001-2005	8	7, 8, 11, 13, 14, 17, 19, 20
	2006-2011	8	8, 14, 15, 18, 21, 22, 23, 24
Type of study	Descriptive	1	8
	Correlational	23	1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24
	Causal/experimental	0	
Sample size	Less than 1,000	2	15, 18
	1,000 - 2,000	1	24
	2,000 - 3,000	3	1, 2, 12
	3,000 - 4,000	2	9, 10
	4,000-5,000	0	
	5,000 - 10,000	5	3, 17, 20, 22, 23
	Greater than 10,000	11	4, 5, 6, 7, 8, 11, 13, 14, 16, 19, 21
Determinants subject to examination	**Education related determinants - individual level**		
	Field of study	9	4, 5, 6, 7, 14, 15, 17, 18, 22
	Level of education	8	4, 5, 6, 7, 15, 17, 18, 19
	Attending vocational education	2	18, 21
	Type of vocational education	2	1, 4
	Work experience during studies	2	18, 22
	Major activity before programme enrolment	1	17
	Time devoted to studies	2	15, 17
	Study programme's prestige	1	18
	Education related determinants - country level		
	Timing of academic specialization	1	16
	Vocational orientation education system	1	21
	Strength institutional linkages	1	21
	Labour market related determinants		
	State economy	2	4, 7
	Job search duration	1	22
	Opportunity structure	1	1
	Job related determinants		
	Job tenure	3	1, 4, 18
	Occupational group	3	1, 15, 19

	Type of employment contract	3	4, 17, 22
	Sector	2	4, 14
	Firm size	3	1, 4, 18
	Occupational 'cultures of training'	1	1
	Method to obtain employment	1	17
	Individual related determinants		
	Gender	11	1, 4, 5, 6, 7, 14, 15, 17, 18, 19, 22
	Age	10	1, 4, 5, 6, 7, 14, 17, 18, 19, 22
	Ethnicity	5	5, 6, 7, 17, 19
	Disability	3	5, 6, 14
	Marital status	3	5, 6, 19
	Job mobility	2	7, 22
	Parental education	2	17, 22
	Ability	2	17, 18
Effects subject to examination	Wage	13	1, 2, 3, 5, 6, 9, 11, 12, 13, 14, 19, 23, 24
	On-the-job search	5	2, 4, 9, 13, 24
	Occupational status	1	4
	Training participation	1	4
	Job satisfaction	5	2, 9, 13, 19, 24
	Field of study regret	2	10, 20

Note: studies can fall into more than one subcategory. a. An overview of the examined countries can be found in Appendix 1. The numbers in the last column of the table refer to 1 of the 24 studies for which more detailed information is provided in Appendix1.

3. Results

3.1. Measurement of horizontal mismatch

Horizontal mismatch is usually defined by comparing an employee's attended field of study with the field required for the job the employee holds. Most of the academic studies on mismatch consider educational attainment as a proxy for the knowledge and skills a worker possesses. However, the skills that are being taught in formal education often only partially overlap with the knowledge and skills that are required in the job (Allen & Van der Velden, 2001). Nevertheless, if skill adjustments are considered as coming with recent graduates to the job, formal education is expected to provide graduates who employers would like to hire (Rogerson, Shimer & Wright, 2005). This suggests that it would be fruitful to investigate the extent to which mismatches between the attended field of education and the job are present on the labour market and what its determinants and consequences are.

The literature on horizontal mismatch distinguishes between 'subjective' and 'objective' definitions. The subjective approach measures the educational requirements for a job based on employees' self-report. The objective method, on the other hand, determines the educational requirements for an occupation using an expert or by assigning occupational codes for statistical purposes to educational fields.

3.1.1. Subjective measure

In many subjective specifications of horizontal mismatch, the respondent specifies the job requirements in terms of the attended field of education. For instance, Kucel and Vilalta-Bufí (2013) classified employees as horizontally matched if s/he reported that exclusively the own attended field or a related field was appropriate for the job, whilst employees were classified as horizontally mismatched when a completely different field or no particular field was most appropriate for the job. Other studies based their definition on the degree to which employees perceive a fit between their field degree and their current job. An example of a question aiming at measuring this degree is: 'Thinking about the relationship between your work and your education, to what extent is your work related to your doctoral degree? Was it closely related, somewhat related, or not related?' (see for instance Bender & Heywood, 2011; Bender & Roche, 2013; Robst, 2007a; Robst, 2007b).

3.1.2. Objective measure

In addition to employees' self-assessment, several studies used an objective indicator of horizontal mismatch. Béduwé and Giret (2011) derived horizontal mismatch measures from a normative correspondence table established by experts. This table categorizes the distinct areas of vocational knowledge into 25 groups to which both educational qualifications and occupations can belong. When the knowledge group of the field degree and occupation do not correspond, there is 'horizontal mismatch'. Other studies use the International Standard Classification of Occupations to assign occupational codes to a field of study (e.g., Wolbers, 2003). The matching process is based on the extent to which the skills acquired through a specific field degree correspond to the job requirements. Accordingly, a discrepancy between the skills obtained in initial education and the skills needed on the job is considered as horizontal mismatch.

The potential advantage of the subjective approach is that it is specifically concerned with the content of the respondent's job and not with any type of aggregate of that occupation. In contrast, the normative correspondence table used by Béduwé and Giret (2011) allows occupations and educational qualifications to be categorized into only 25 groups. Some occupations or educational qualifications will better fit into one of the categories than others. Having too many categories, however, increases the likelihood that the combination of jobs and field degrees are defined as mismatched despite a large congruence of skills and knowledge (Malamud, 2011). Therefore, the subjective approach might provide

a more valid measure of horizontal mismatch as employees' field degree is directly compared with the content or the educational requirements for the job. A potential disadvantage of the subjective method is that employees' perception of horizontal match is by definition subject to self-report bias. From this perspective, a method such as the normative correspondence table can provide a less biased indicator of horizontal mismatch. Moreover, asking employees whether their field degree was a requirement for the job might also not be the best indicator for horizontal mismatch. Some employers might simply require more general skills that can be obtained through various fields of study. Hence, the validity of these subjective measures can be called into question.

It is noteworthy that horizontal mismatch is being measured in a similar manner across graduates who have attended different fields of education. While some fields clearly prepare students for specific occupations, such as medicine and law, other fields are more general in nature like arts. Consequently, some professions require their workers to have attended a specific field that provides students with occupation-specific skills and knowledge, whereas other occupations require graduates to possess more general skills that can be acquired through a variety of study programmes. Hence, comparing job applicants' acquired field degree to the educational requirements for the jobs can be inappropriate if one wants to reveal skill mismatches, especially if the attended field does not prepare student for a specific occupation. We will return to this issue several times in this paper.

3.2. Prevalence of horizontal mismatch

Table 2 summarizes the findings of the 20 studies that report the incidence of horizontal mismatch. Not all 24 studies selected for our review estimated the prevalence of horizontal mismatch. The literature identifies at least four ways to measure horizontal mismatch: definition A - based on employees' assessment of whether a specific field of education was required for the job or not; definition B - based on employees' assessment of whether their attended field of education is related to or relevant for their current occupation; definition C - respondents' assessment of whether or not they have been trained for their current job; and definition D - based on an objective evaluation where occupations and educational fields are categorized according to the assumed congruence between the skills acquired through the field degree and the skills needed to perform a specific occupation.

Table 2 shows that there is considerable variation in the mismatch incidence reported by the studies under review. Note that some studies made a distinction between severely mismatched and moderately

mismatched employees when reporting the incidence rate of mismatched employees (e.g., Robst, 2007a; Robst, 2007b), whereas other studies combined such categories into one (e.g., Allen & Van der Velden, 2001). The incidence reported by the studies under review vary from 7 to 63 percent. The incidence, however, seems to depend on how horizontal mismatch is specified. For instance, Malamud (2011) found 63 percent of employees in England to be mismatched when using a narrow classification and an incidence rate of 44 percent based on a very broad classification. Whilst the narrow classification allows fields and occupations to be categorized into 42 categories, the very broad classification distinguishes 6 categories. Hence, employees are more likely to be defined as mismatched according to the narrow classification.

On average, studies using definition A find that almost 21 percent of the employees are horizontally mismatched. According to definition B, 21.8 percent of the employees hold a field degree that is either only somewhat relevant or only slightly relevant for the job they hold (column 4). Based on the same definition, 23.3 percent of the employees hold a degree that is either somewhat relevant or completely irrelevant for their job (column 5). One study used definition C and found that 46 percent of the employees are in a job for which they have not been trained. Finally, according to definition D, 22.1 percent of the employees hold an occupation for which their field has some relevance (column 4). Again adopting definition D, column 5 shows that 35.4 percent of the employees are fully mismatched or hold a degree that only has low relevance for their job. Table 2 also separately depicts the incidence of horizontal mismatch for men, women, different career stages, countries, different types of employment and for various reasons for accepting horizontal mismatch. We discuss how these variables relate to horizontal mismatch in more detail in the next sections.

Table 2: Incidence of Horizontal Mismatch

Author (year of publication)	Country of study and definition[a]		Year data collection	Moderately mismatched (male/female) (%)	Severely mismatched (male/female) (%)	Incidence of horizontal mismatch for other sample characteristics
Witte et al. (1995)	Germany	C	1984–1990		Not trained for job: 46.35 (51.0/39.0)	
Allen et al. (2001)	The Netherlands	A	1998		Own/related field not most appropriate: ±20.0	
Robst (2007a, 2007b)[b]	United States	B	1993	Somewhat related: 25.1 (28.3/20.8)	Not related: 20.1 (19.1/21.4)	*Most important reason for accepting HM (male/female) (%):* -Pay, promotion: 32.7/18.8 -Working conditions:8.8/11.1 -Job location: 4.3/3.5 -Change career interests: 19.0/19.3 -Family-related: 5.9/18.1 -Job in field degree unavailable: 16.0/16.3
Hensen et al. (2009)	The Netherlands	B	1996–2001		Own/related field not most appropriate: 30.0 (29.0/30.0)	
Mora (2010)	Spain	A	2000		No specific field required: 18.95	
Nordin et al. (2010)	Sweden	D	2003	Weak match: 11.67 (18.0/8.0)	Mismatch: 19.2 (23.0/17.0)	
Yakusheva (2010)	United States	D	1980, 1984, 1986, 1992	Knowledge associated with field has medium relevance for job: 32.45	'' low relevance '': 14.55	
Béduwé et al. (2011)	France	D	2001		59.0	-No VM but HM: 30 -VM and HM: 29
Bender et al. (2011)	United States	B	1993, 1995, 1997, 1999, 2001, 2003, 2006	Somewhat matched: 24.7 (25.5/22.5)	Severely mismatched: 8.0 (8.3/7.0)	-Somewhat matched in early career: 22.8 -'' in middle '': 25.3 -'' in late '': 26.8 -Severely mismatched in early career: 5.9 -'' in middle '': 8.5 -'' in late '': 10.2 *Most important reason for accepting HM (early career/late career stage) (%):* -Pay, promotion: 22.1/19.3 -Working conditions: 5.1/4.9 -Job location: 4.6/5.2 -Change career interests: 25.6/38.9 -Family-related: 8.1/4.6 -Job in field degree unavailable: 26.7/18.3

Table 2 continued

Farooq (2011)	Pakistan	B	2006/2007, 2008/2009	-Slightly relevant: 13.8 (18.5/12.9)	-Irrelevant: 11.3 (14.8/10.6)
Malamud (2010, 2011) [b]	England and Scotland	D [c]	2011		Overall average: 45.17 -Very broad classification England: 44.0 -Broad classification England: 50.0 -Narrow classification England: 63.0 -Very broad classification Scotland: 29.0 -Broad classification Scotland: 34.0 -Narrow classification Scotland: 51.0
Boudarbat et al. (2012)	Canada	B	2005		Somewhat/not closely related: 35.1
Kucel et al. (2012)	Poland	A	2008		Other/ no specific field required: 18.0
Kucel et al. (2013)	Spain and The Netherlands	A	2005		Other/ no specific field required: -Spain: 27.0 -Netherlands: 20.0
Bender et al. (2013)	United States	B	2003	Overall weighted average: 23.64 -Moderately mismatched wage/salary employees: 23.7 (25.5/21.0) -Moderately mismatched self-employed: 23.3 (24.0/21.5)	Overall weighted average: 14.2 -Severely mismatched wage/salary employees: 13.3 (13.2/13.5) -Severely mismatched self-employed: 19.4 (17.5/24.4)
Levels et al. (2014)	20 countries[d]	D			38.8
Zhu (2014)	China	B	2008		Not related: 28.16 (27.2/29.7)
Shevchuk et al. (2015)	Russia	B	2011		Job fully/mostly mismatches 39.31 (43.4/35.6)

A. based on self-report of whether a specific field of education was required for the job B. based on respondents' assessment of the extent to which their attended field of is related to or relevant for their current occupation C. respondents' assessment of whether or not they have been trained for their current employment D. objective measure. b. Note that these are two separate studies using the same dataset, we therefore we report the incidence of horizontal mismatch found in these studies once. c. Occupations and fields of study are categorized according to three gradations of classification: narrow (42 categories), broad (12 categories) and very broad (6 categories). An employee is defined to be horizontally mismatched when the field and occupation fall into different categories. Most analyses are based on the broad classification, but are robust to alternative classifications. d. Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Finland, France, Greece, Hungary, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Sweden, Slovenia, Slovak Republic and the UK.

3.3. Determinants of horizontal mismatch

In this section, we report which variables were considered potential determinants of horizontal mismatch in the studies under review and whether a positive, negative, or no relationship was found. The findings are summarized in Table 4 and are categorized into education-, labour market-, job-, and individual-related determinants. We limit our discussion to those determinants that have been investigated by at least two studies. The determinants that were subject to examination in only one study can be found in Appendix 1.

3.3.1. Education related determinants

Several factors predicting horizontal mismatch relate to the education the individual has received. The education-related factors can be classified at two levels; the individual level and the country level. With education-related determinants on the individual level we refer to factors that can be considered an individual's choice such as the field and level of education. In contrast, education-related determinants on the country level are rather exogenous to the individual and may for instance pertain to the vocational orientation of a country's education system.

3.3.1.1. Education related determinants at the individual level

The prevalence of horizontal mismatch among graduates depends among other things on the characteristics of the attended study programme. With respect to the field degree, the highest mismatch rates are found among liberal arts graduates, whilst the mismatch rates are lowest for graduates from health related fields (Robst, 2007a; Wolbers, 2003). Health related fields mainly provide students with occupation-specific skills which reduces the likelihood that graduates search for jobs outside their own field (Wolbers, 2003). The probability that horizontal mismatch occurs across the career stage also depends on the attended field degree. This can be attributed to the pace of human capital depreciation associated with the field of study (Bender & Heywood, 2001). For instance, science- and engineer-based careers are more sensitive to mismatch due to the high frequency of technological changes which induce rapidly changing skill requirements (Bender & Heywood, 2001).

Besides the field degree, the likelihood of being horizontally mismatched is determined by graduates' level of education (Bender & Roche, 2013; Boudarbat & Chernoff, 2012; Hensen, De Vries & Cörvers,

2011; Robst, 2007a; Wolbers, 2003). Employees who are not able to find a job that matches their level of education might compete with less-educated employees for a job below their level but in a related field (Borghans & De Grip, 2000). Given that the less-educated face fewer jobs for which they can deploy this strategy, accepting a job in a different field is more likely to be an alternative strategy for this group when a matching job is unavailable.

Although the level of education is negatively related to horizontal mismatch, at the same time, higher levels of education are often more general in nature. General skills lend themselves to a wider variety of jobs which positively relates to one's chances to end up in a job not directly related to the field degree. Vocational programmes, on the other hand, provide students predominantly with occupation-specific skills, creating a stronger link between the field degree and the jobs for which students are being prepared. As such, school leavers with a vocational degree are more likely to be horizontally matched than graduates without a vocational training (Levels, Van der Velden & Di Stasio, 2014). Since both the vocational orientation of study programmes as well as the level of education influence the probability of being matched, it might be worthwhile to distinguish between workers with different levels of education when measuring horizontal mismatch.

Also the type of vocational system influences horizontal mismatch. Employers can substantially reduce selection and allocation costs by hiring graduates who received workplace-based or apprenticeship training in their organization (Wolbers, 2003). Hiring these graduates removes the need for screening and has the advantage of employing employees who already have acquired firm-specific skills. However, Wolbers (2003) did not find that workplace-based or apprenticeship training offered vocational graduates significant benefits in terms of finding a matching job compared to students with no vocational education. However, in this study, graduates who did not attend vocational education might be more likely to have acquired higher levels of education. Hence, the results might simply reflect that the effect of the attended level of education on horizontal mismatch outweighs the effect of having attended vocational education.

In addition to study programme characteristics, horizontal mismatch is determined by whether students were enrolled in a part-time or full-time programme. Several studies found that graduates who studied full-time are more likely to obtain a job that matches their field compared to graduates who studied part-time (Boudarbat & Chernoff, 2012; Farooq, 2011).

3.3.1.2. Education related determinants at the country level

The studies under review identified three factors that characterize a country's education system which in turn determine horizontal mismatch; the timing of academic specialization, the vocational orientation, and the strength of institutional linkages. Regarding the timing of academic specialization, late specialization might induce graduates more to switch to an unrelated occupation as the costs of not utilizing specific skills are lower than for graduates who specialized early. On the other hand, later specialization also offers students more time to acquire valuable information about their preferences and abilities by taking courses in different fields. Hence, later specialization conceivably provides students more insight into the probability of obtaining a field-related occupation given the acquisition of a specific field degree. Malamud (2011) found support for the second hypothesis as graduates who attended the Scottish education system, which is characterized by late specialization, are less likely to hold a job unrelated to the field of study compared to graduates from the English education system in which students specialize early.

Also the extent to which an education system is vocationally oriented is strongly country-dependent. Wolbers (2003) defined countries as being more vocationally oriented when the share of upper secondary education students, who are enrolled in school-based or apprentice-type of vocational education, is larger. Although the results were insignificant, graduates were found to be more often mismatched in vocationally oriented countries. Levels et al. (2014) also found that the horizontal mismatch incidence is greater in countries with a strong vocational orientation. Arguably, competition between graduates with a vocational degree is fiercer in countries with a large share of vocationally educated employees.

However, the relation between horizontal mismatch and a vocationally oriented education system can be positive in countries with strong institutional linkages (Levels et al., 2014). The strength of institutional linkages is reflected by the share of vocational education that is organized as a combination of school-based education and training at the workplace (Breen, 2005). Countries with strong institutional linkages provide employers an opportunity to teach students skills that are required by existing jobs (Andersen & Van de Werfhorst, 2010). Moreover, strong institutional linkages allow employers to design jobs in a way such that it meets the expected skills of vocational graduates.

This section has discussed education-related determinants of mismatch. What can be noticed is that several education-related determinants of mismatch share similar properties. The field and level of education, having attended vocational education, the vocational orientation of a country's education system and the strength of institutional linkages within a country all determine the degree to which graduates acquire occupation-specific or general skills. Graduates who predominantly obtained occupation-specific skills are more likely to end up in a job that is closely related to their field degree. Although graduates who mainly acquired general skills are more likely to be horizontally mismatched according to the definitions identified in the literature, their skills are valued in a wider variety of jobs. The degree to which horizontal mismatch among graduates with general education is accompanied by skill-underutilization might therefore be smaller than most definitions actually suggest. According to the human capital theory, general skills increase workers' productivity in a wider range of occupations than specific skills (Becker, 1964). In fact, as Section 6 will point out, the wage penalties incurred by employees who received general education are less severe as opposed to those who received more occupation-specific education.

3.3.2. Labour market related determinants

Once students complete formal education, labour market conditions influence graduates' chances of finding a matching job. Graduates who face an economic recession upon labour market entry adjust their goals and are more likely to accept a job that does not match their field of education (Wolbers, 2003). Hensen et al. (2011) did not find a relation between the regional unemployment rate and horizontal mismatch.

Another measure for the state of the economy is the opportunity structure. The opportunity structure refers to the number and type of available vacancies and how well an employee's and other potential job candidates' skills match the requirements for a job (Witte & Kalleberg, 1995). Witte and Kalleberg (1995) found that fluctuations in the opportunity structure negatively influence the probability for women to hold a job that matches their field degree, but not for men. Also the search duration to find the first job increases the odds of being horizontally mismatched (Robert, 2014).

3.3.3. Job related determinants

Once graduates are employed, job-related factors influence the probability of being horizontally matched. Employees' tenure appears to be negatively related to horizontal mismatch (Witte &

Kalleberg, 1995; Wolbers, 2003). A potential explanation for this finding is that once employees find a job that matches their education and the returns to schooling meet a certain level, employees will not be incentivized to change jobs (Witte & Kalleberg, 1995). Another possible explanation is that as job tenure increases, employees accumulate firm-specific skills which are less attractive to other firms. Consequently, it is more difficult for mismatched employees with a longer tenure to search for a matching job outside the firm.

Also graduates with a temporary contract are more likely to be mismatched than employees with a permanent contract (Boudarbat & Chernoff, 2012; Wolbers, 2003). Temporary jobs offer limited opportunities to acquire relevant work experience and productive skills as opposed to permanent employment. Given that employees with a temporary contract are expected to leave the company earlier, employers are generally reluctant to offer company-funded training due to the shorter payback period of such investments (Becker, 1964; Booth, Francesconi & Frank, 2002). Consequently, job-education mismatch can serve as a compensation for the lack of human capital that is typically gained through on-the-job training and work experience (Groot & Maassen van den Brink, 1996). Robert (2014) found that the odds of being horizontally mismatched are higher for employees with a permanent contract than for employees with a fixed term contract or self-employed employees. Arguably, employees might also accept horizontal mismatch in return for job safety provided by a permanent contract.

Variations in the prevalence of horizontal mismatch are also found across occupational groups and sectors. Bender and Roche (2013) indicated that self-employed workers are more likely to be severely mismatched than wage or salary workers.[2] Whilst self-employed men are more likely to be mismatched predominantly due to working conditions, self-employed women tend to accept horizontal mismatch mainly for family-related reasons. Employees in specialized occupations; managers, professionals, associate professionals, and women in white-collar jobs are less likely to be horizontally mismatched than employees in elementary occupations (Farooq, 2001; Witte & Kalleberg, 1995). This can be explained by the fact that the duties and requirements for white-collar occupations, also in terms of the education acquired, are less specifically defined.

[2] The results are robust to heterogeneity between the self-employed, wage-, and salary workers (choosing self-employment to obtain a better work-life balance or due to prior labour market experiences). Moreover, the results are robust to selection into self-employment because of previously being mismatched in a wage or salary job. The results also remain unchanged when managers are left out of the dataset. Employees who climb up the career ladder into management use skills that deviate from those acquired through formal education.

With respect to the sector in which individuals are employed, the likelihood of horizontal match is greater in the public sector than in the private sector (Wolbers, 2003). This can be attributed to the fact that the public sector consists of all healthcare and educational organizations which, on average, employ more graduates who received vocationally oriented education.

With respect to firm characteristics, being employed in a large firm can provide a relatively large set of opportunities to find a matching job (Hamilton, 1987). Wolbers (2003) found that employees in larger firms are more likely to be well-matched. Contrariwise, Witte and Kalleberg (1995) found that the likelihood of horizontal mismatch for men increases with the size of the firm (Witte & Kalleberg, 1995). Arguably, individuals employed in large firms might be more incentivized to accept horizontal mismatch due to higher wages, job security, and other job advantages offered by large firms (Kalleberg & Van Buren, 1992).

3.3.4. Individual determinants

Finally, several characteristics related to the individual influence employees' labour market outcomes. For instance, labour market prospects and outcomes are found to differ between men and women along various dimensions (Altonji & Blank, 1999). This also holds for obtaining a job that matches one's field degree. Bender and Heywood (2011) demonstrate that males are more likely to be mismatched than females. However, as the findings apply to PhD graduates in a science, mathematics, or engineering field, these results cannot be generalized. Other studies provide evidence that females are more likely to be mismatched as opposed to their male counterparts (Farooq, 2011; Hensen et al., 2009). For men, mismatch is more likely to be the result of career-oriented reasons like pay and promotion opportunities, or changing career interests, whilst women are more likely to report mismatch due to family-related reasons, the job location, or working conditions (Bender & Heywood, 2011; Robst, 2007b). Bender and Roche (2013) found that in the wage and salary sector, women are less likely to be severely mismatched than their male counterparts. In contrast, self-employed women are more likely to be severely mismatched than self-employed men.

The probability of being horizontally mismatched also relates to employees' age (Bender & Roche, 2013; Wolbers, 2003). Using a panel framework, Bender and Heywood (2011) demonstrated that employees are most likely to make the transition from a state of mismatch to a state of match in early stages of their career. This is consistent with the idea that mismatch is a result of employees' career evolution and

not necessarily an indicator of labour market inefficiency. Besides the fact that career interests might change over time, the value of the stock of human capital accumulated through formal education depreciates over time and reinvesting in rapidly depreciating skills becomes less attractive as the length of the payback period shortens. Moreover, the skills acquired through vocational education become less relevant over time in the presence of technological changes (Witte & Kalleberg, 1995). Hensen et al. (2009), on the other hand, found that employees' age is positively associated with holding a job that matches the field of education. Robert (2014) also found a negative relation between horizontal mismatch and age; however, this effect vanishes when the sample is reduced to respondents who left their first job. As the latter two studies use samples consisting of recent graduates, it appears that it takes some employees more time to find an appropriate job upon labour market entry. After some point, however, the probability of becoming horizontally mismatched arguably increases.

In addition to gender and age, a substantial amount of studies point at the presence of racial differentials in labour market outcomes (e.g., Altonji & Blank, 1999; Boudarbat & Chernoff, 2012; Hensen et al. 2011). Empirical evidence suggests that compared to white employees, the likelihood of being horizontally mismatched is higher for Asian men and lower for black employees and Hispanics (Bender & Roche, 2013; Robst, 2007a). Black employees are more likely to be mismatched because a related job was unavailable, whilst they are less likely to report mismatch as a result of the job conditions, changing career interests, or family-related reasons.[3]

An individual factor that strongly predicts educational as well as labour market outcomes is individuals' ability. Graduates in lower grade categories are significantly less likely to find a job that relates to the field of study compared to graduates in the highest grade category (Boudarbat & Chernoff, 2012; Kucel & Vilalta-Bufí, 2012). Employers could use high grades as a signal for the quality of an individual's subject-related skills.

In addition to individual-related determinants that are exogenously determined, individuals make choices that affect their labour market outcomes (Büchel & Van Ham, 200). One might hypothesize that the extent to which employees are willing to seek for a job outside the place of residence reduces the probability of an education-job mismatch. However, geographic mobility or intensive job shifts has a

[3] Robst (2007b) used the same dataset as Robst (2007a). Robst (2007a) found, compared to white employees, a significant positive effect for Asian men, but no effect for women. Furthermore, where Robst (2007a) found a significant negative effect for black employees, Robst (2007b) found no significant differences between white and black employees.

negative effect on the likelihood of being horizontally matched (Hensen et al., 2009; Robert, 2014). This might suggest that intensive job search merely reflects an instable labour market position.

Finally, disabled employees face a higher chance of obtaining a job that does not match the attended field of education (Bender & Heywood, 2011; Robst, 2007a). The difference between the disabled and the non-disabled is particularly evident when a job is accepted outside the field degree for the reason that a related job was not available (Robst, 2007a). For employees in their late career stage, Bender and Heywood (2011) found no effect. Regarding individuals' marital status, individuals who are not or have never been married are more likely to be mismatched than employees who are married (Bender & Roche, 2013; Robst, 2007a).[4]

While the studies under review offer an extensive list of factors determining the likelihood that individuals experience horizontal mismatch, the relation between the identified determinants and horizontal mismatch might also interact in many ways that are not assessed by the papers included in this review. For instance, Robst (2007b) indicates that women are more likely to experience mismatch due to family-related reasons. Given that family-related reasons are more likely to play a role at a certain age, age interacts with the relation between horizontal mismatch and gender. Given that the articles included in this review dealt with different countries, findings on how variables such as gender and race relate to horizontal mismatch might also be influenced by country norms. Finally, the incidence of horizontal mismatch changes over time as the demand and supply of skills in the labour markets is not time constant (Goldin & Katz, 1996).

[4] In contrast to Robst (2007a), Robst (2007b) found that employees who have never been married are less likely to be mismatched.

Table 3: Parameter Estimates of the Determinants of Horizontal Mismatch (= treated as the outcome variable here)

Author (year publication)	Country of study and definition used[a]		Education-related determinants - Individual level							
			Field of study	Level of educ.	Voca-tional educ.	Type of vocational education (men/women)	Work experience during studies (ref. cat.=no work experience)	Major activity before entering university (ref. cat.=not working/ studying)	Time devoted to studies (ref. cat.=full-time)	Study pro-gramme's prestige as a signal of quality
Witte et al. (1995)	Germany	C				Ref. cat=school-based vocational education -Industrial apprenticeship: +/n.e. -Commercial apprenticeship: +/n.e.				
Wolbers (2003)	13 countries[b]	D	s.e.	-		Ref. cat.=no vocational educ.: n.e.				
Robst (2007a)	United States	B	s.e.	-						
Hensen et al. (2011)	The Netherlands	B	s.e.	-						
Bender et al. (2011)	United States	B	s.e.							
Farooq (2011)	Pakistan	B	s.e.	n.e.					Part-time:+	
Malamud (2011)	England and Scotland	D	s.e.							
Boudarbat et al. (2012)	Canada	B	s.e.	-				-Studying: + -Working: + -Studying and working: +	-Part-time: + -Mix part-time and full-time: +	
Kucel et al. (2012)	Poland	A	s.e.	n.e.	n.e.		Internship: n.e.			-Employers familiar: - -Prestigious: -
Bender et al. (2013)	United States	B		-						
Levels et al. (2014)	20 countries[c]	D			-					
Robert (2014)	Hungary, Poland, Lithuania and Slovenia	A	s.e.				-Study-related work experience: - -Not study-related work experience: +			

Table 3 Continued

Author (year of publication)	Country of study and definition used[a]		Education-related determinants - Country level			Labour market-related determinants		
			Time of academic specialization (ref. cat.=early specialization)	Vocational orientation education system	Strength institutional linkages	State of the economy (unemployment rate)	Opportunity structure[d] (men/women)	Job search duration
Witte et al. (1995)	Germany	C					Ratio unemployed employees to number of available vacancies for a specific occupational group: n.e./+	
Wolbers (2003)	13 countries[b]	D		-Share of upper secondary students in school-based vocational education: + -'' in apprenticeship type vocational education: n.e.		+		
Hensen et al. (2011)	The Netherlands	B				n.e.		
Malamud (2011)	England and Scotland	D	Late specialization: -					
Levels et al. (2014)	20 countries[c]	D		+ Interaction vocational orientation ×vocational education: n.e.	- Interaction institutional linkages × vocational education: -			
Robert (2014)	Hungary, Poland, Lithuania and Slovenia	A						+

Table 3 Continued

Author (year of pub.)	Country of study and definition used[a]		Job-related determinants						
			Job te-nure	Type of contract (ref. cat. = permanent/full-time contract)	Occupational group (men/women)	Occupational cultures of training (men/ women)	Sector (early career/late career)	Firm size (men/ women)	Method to obtain employment
Witte et al. (1995)	Germany	C	-		Ref. cat=blue-collar -White-collar: n.e./- -Civil servants: n.e./-	-/n.e.		+/n.e.	
Wolbers (2003)	13 countries[b]	D	-	-Part-time: + -Fixed term '': +			Ref.cat.=private -Public: -	-	
Bender et al. (2011)	United States	B					Ref. cat=academia Government:+/n.e. Business: +/n.e.		
Farooq (2011)	Pakistan	B			Ref.cat=employees in elementary occupations: -Manager: - -Professional: - -Associate professional: -				
Boudarbat et al. (2012)	Canada	B		-Part-time: + -Fixed term: n.e.					Ref.cat.=referred by someone: -Answered job ad: n.e. -Directly contacted employer: n.e. -Campus placement agency:- -Employment agency: n.e. -Head hunter: n.e.
Kucel et al. (2012)	Poland	A	n.e.					n.e.	
Bender et al. (2013)	United States	B			Ref. cat=wage and salary employees: -Severely mismatched self-employed: +				
Robert (2014)	Hungary, Poland, Lithuania and Slovenia	A		Temporary/ part-time: -					

Table 3 Continued

Author (year of pub.)	Country of study and definition used[a]		Individual-related determinants							
			Gender (ref. cat.= women)	Age	Abi-lity	Parental education	Ethnicity (men/women)	Job mobility	Marital status (ref. cat.= married)	Dis-ability
Witte et al. (1995)	Germany	C	+	+						
Wolbers (2003)	13 countries[b]	D	+	+						
Robst (2007a)	United States	B	+	+			Ref. cat.=white: -Asians: +/n.e. -Black: - -Native Americans:n.e. -Hispanics: -		+	+
Robst (2007b)	United States	B	+							
Hensen et al. (2011)	The Netherlands	B	-	-			Ref. cat.=natives: -Immigrants: +	Geographic:+		
Bender et al. (2011)	United States	B	+	+						n.e.
Farooq (2011)	Pakistan	B	-							
Boudarbat et al. (2012)	Canada	B	n.e.	n.e.	-	Ref. cat.=parents with less than secondary education: -Secondary: n.e. -Some postsecondary: n.e. -Trade: + -Postsecondary: n.e. -Bachelor: n.e. -Postgrad: n.e.	Ref. cat.=natives: -Immigrants: +			
Kucel et al. (2012)	Poland	A	n.e.	n.e.	-					
Bender et al. (2013)	United States	B	-Wage employees: + -Self-employed: -	+			Ref. cat=white: -Asians: n.e. -Black: n.e. -Hispanics: -		+	
Robert (2014)	Hungary, Poland, Lithuania and Slovenia	A	n.e.	n.e.		Ref. cat.=parents with ISCED 5-6: -ISCED 3-4: + -ISCED 1-2: n.e.		-Number of jobs: + -Left first job: n.e.		

Note: + indicates a positive relation between horizontal mismatch and the determinant, – indicates a negative relation, and n.e. indicates that no effect was found. a. Definition of horizontal mismatch: A. based on self-report on whether a specific field of education was required for the job B. based on respondents' assessment of the extent to which their current occupation is related to their attended field of education C. based on respondents' assessment of whether or not they have been trained for their current employment D. objective measure. b. The 13 countries comprise Austria, Belgium, Denmark, Spain, Finland, France, Greece, Hungary, Italy, Luxembourg, The Netherlands, Sweden and Slovenia. c. The 20 countries comprise Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Finland, France, Greece, Hungary, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Sweden, Slovenia, Slovak Republic and the UK.

3.4. Outcomes associated with horizontal mismatch

Table 4 provides an overview of the outcomes associated with horizontal mismatch. As Table 4 depicts, a substantial amount of economic research has been conducted on the relation between horizontal mismatch and employees' earnings. Social stratification research, on the other hand, has been concerned with the association between horizontal mismatch and employees' occupational status. Furthermore, the studies selected for our review have examined what horizontal mismatch implies for on-the-job search, training participation, job satisfaction and regret of the chosen field of study.

Most studies assessing the wage implications of horizontal mismatch compare well-matched employees to their mismatched counterparts who hold the same field degree. Employees who are horizontally mismatched generally incur a wage penalty. Some employees, despite being mismatched, are still able to utilize some of the skills acquired through their field degree and, therefore, only incur small wage penalties (Bender & Heywood, 2011; Bender & Roche, 2013; Nordin, Persson & Rooth, 2010; Robst, 2007b; Yakusheva, 2010). Robst (2007b) showed that whereas mismatched men receive a wage penalty of 11.9 percent, partially mismatched men only incur a wage loss of 2.9 percent. The wage penalties incurred by mismatched and partially mismatched women are 10.1 and 2.1 percent, respectively.

The wage effect differs across reasons for accepting horizontal mismatch (Robst, 2007a). The wage loss accompanied with horizontal mismatch because of the job location or family-related reasons, ranges from 18.1 to 29.3 percent for men and from 17.2 to 21.5 percent for women (Robst, 2007a). The pay penalties associated with the inability to find a matching job is 18.5 percent for females and 26.5 percent for men. In contrast, accepting horizontal mismatch because of pay and promotion opportunities is associated with a wage gain of 9.1 percent for women and 6.1 percent for men (Robst, 2007a). Hence, accepting horizontal mismatch does not always have negative wage consequences. Similarly, Zhu (2014) showed that 32.3 percent of the Chinese college graduates benefit from being horizontally mismatched as they receive a wage premium.

The wage effects also vary among employees in different types of employment. Compared to matched wage and salary workers, the severely mismatched self-employed incur wage penalties twice as large as mismatched wage and salary workers (Bender & Roche, 2013).[5] In line with Robst (2007a), the greatest

[5] These results were obtained whilst including heterogeneity controls, that is, having children between the age of 6 and 11 and previous labour market experiences.

wage penalties are incurred when a matching job is unavailable. Mismatch also carries different wage penalties depending on employees' career stage. Bender and Heywood (2011) found greater wage penalties for mismatched employees later in their career stage than for those in the early stage of their career. As older mismatched employees are being compared with well-matched employees in the reward phase of their earnings profile, employees in later stages of their career face larger wage penalties in comparison to employees early in their career.

Zhu (2014) found relatively small wage penalties, namely, 1.2 percent for men and 1.5 percent for women. Zhu (2014) attributed these small wage losses to the strong emphasis of the Chinese education system on providing students general skills.[6] Such skills are believed to be transferable and rewarded in all occupations. Similarly, Nordin et al. (2012) argued that although employees who attended a field that mainly provides job-specific skills are less likely to be horizontally mismatched, they generally incur a larger wage penalty than employees who predominantly acquired general skills through their field of study. In fact, graduates with a degree in medicine, which is known to provide highly job-specific skills, suffer from the largest wage losses when experiencing horizontal mismatch (Zhu, 2014). Having a major in literature, on the other hand, provides rather general skills and is associated with the smallest wage penalties in the case of mismatch (Zhu, 2014).

In order to offset initial skill deficiencies, employees who are horizontally mismatched upon labour market entry might acquire additional skills on the job. Nordin et al. (2010) showed that the return to work experience for mismatched men is significantly greater than for well-matched men. This supports the idea that mismatched employees reduce their initially incurred wage penalty by gaining relevant skills on the job. Likewise, Malamud (2010) showed that being mismatched in the first year after graduation yields a wage loss of 7 percentage points. However, compared to graduates who are matched upon labour market entry, initially mismatched employees do not significantly earn lower wages six years after graduation. This suggests that horizontal mismatch is only a temporary phenomenon.

According to the job search theory, mismatched employees might also try to improve their fit by changing jobs until an optimal match is reached (Jovanovic, 1979). The probability to look for another job appears to be larger for employees who are horizontally mismatched than for well-matched

[6] Zhu (2014) employs a nonparametric model. The wage penalty associated with horizontal mismatch was found to be much larger with the OLS approach, namely, 5.9 percent.

employees (Béduwé & Giret, 2011; Malamud, 2010; Wolbers, 2003). Moreover, mismatched employees are more actively engaged in job search activities in countries with a low vocational orientation (Wolbers, 2003). This supports the view that vocational education functions as a safety net (Shavit & Müller, 2000), reducing the risk of unemployment or ending up in unskilled employment. Some studies found no relation between horizontal mismatch and on-the-job search (Allen & Van der Velden, 2001; Shevchuk, Strebkov & Davis, 2015).

A different strategy to cope with job-education mismatch is to participate in additional on-the-job training to offset the shortcoming of the skills acquired through initial education (Wolbers, 2003). The idea is that horizontally matched employees more optimally utilize their skills which reduces the need to invest in additional training. Unexpectedly, Wolbers (2003) found that mismatched school-leavers participate significantly less in additional training than their well-matched counterparts. However, the effect of job mismatches on training participation turns out to be positive in countries characterized by low shares of school-based vocational education and apprenticeship trainings. Arguably, graduates who have acquired general education more often receive training on the job to acquire job-specific skills which were not offered through formal education.

Where most economic studies focus on the wage consequences of mismatch, most social stratification research assess what mismatch entails for employees' occupational status. On average, mismatched employees have an occupational status that is lower than for well-matched employees (Wolbers, 2003). The loss in occupational status associated with mismatch is lower in countries characterized by an education system that is more vocationally oriented.

Various studies found a positive relationship between horizontal mismatch and employees' level of job satisfaction. The size of the relation between horizontal mismatch and job satisfaction decreases when controlling for certain job attributes such as having a permanent position or being employed in an organization with large internal labour markets. To put it differently, individuals appear to be willing to accept a job that does not match their field of study in exchange for a job that offers satisfactory perspectives such as job stability and professional development. Bender and Roche (2013) found that the association between mismatch and job satisfaction is weaker for self-employed employees than for wage and salary workers. This could indicate that despite the relative large wage penalties incurred by the mismatched self-employed, accepting horizontal mismatch in the self-employment sector offers job

attributes that compensate for those wage penalties such as greater flexibility in working hours (Benz & Frey, 2008; Connelly, 1992).

Shevchuk et al. (2015) only found a negative association between horizontal mismatch and job satisfaction among women. Allen and Van der Velden (2001) did not find any effect of horizontal mismatch on job satisfaction. However, skill underutilization does appear to negatively affect job satisfaction (Allen & Van der Velden, 2001). Also Béduwé and Giret (2011) found that the horizontal mismatch coefficient reduces in size when including an indicator for skill utilization at the workplace. Hence, it appears to be skill underutilization that leads employees to experience job dissatisfaction. As such, comparing graduates' attended field of study with the educational requirements for the job is not always a perfect proxy for the degree to which employees underutilize field-related skills.

Table 4: Parameter Estimates of the Outcomes Associated with Horizontal Mismatch (= treated as the predictor variable here)

Author (year of pub.)	Country of study and definition used [a]		Rate of return to horizontal mismatch (male/female) (%)	On-the-job search (ref. cat.=no search) (male/female)	Training participa-tion (male/ female)	Occupa-tional status (male/ female)	Job satisfaction (male/ female)	Field study regret (male/ female)
Witte et al. (1995)	Germany	C	-Industrial apprenticeship: n.e. -Commercial apprenticeship: n.e./+ -School-based vocational educ.: n.e./+					
Wolbers (2003)	13 countries[b]	D		-Overall:+ Including HM×vocational orientation country: -	-Overall:- Including HM× vocational orientation country: -	-Overall:- Including HM× vocational orientation country: -		
Allen et al. (2001)	The Netherlands	A	n.e.	n.e.			n.e.	
van de Werfhorst (2002)	The Netherlands	D	-Overall average: -3.48 -'Cultural' related competencies are offered by employee's field of study *and* are demanded by the job: n.e. -'Economic' '': 4.1 -'Communicative' '': 7.1 -'Technical' '' *but not* '' (ref. cat.) -2.7					
Robst (2007a)	United States	B	-Overall:-10.2/-8.9 HM by reason: -Pay, promotion opportunities: 6.1/9.1 -Working conditions: -19.6/-17.2 -Job location: -29.3/-21.1 -Changed career interests: -8.3/4.7 -Family-related reasons: -18.1/-21.5 -No matching job available:-26.5/-18.5					
Robst (2007b)	United States	B	-Field not related: -11.9/-10.1 -Field somewhat related: -2.9/-2.1					
Malamud (2010)	England and Scotland	D	-HM in first year after graduation: -7.0 -HM six years after graduation: n.e.	+			Getting an interesting job: -	
Mora (2010)	Spain	A						n.e.
Nordin et al. (2010)	Sweden	D	-HM: -19.5/-12.2 -Weakly HM: -1.4/-2.9 -HM+field gave specific skills:-19.8/-21.2					

			-HM+field gave general skills:-18.3/-9.1 Controlled for experience: -HM: -6.8/6.9			
Yakushe-va (2010)	United States	D	Ref. cat.= degree has low relevance -Highly relevant degree: 21.2 -Medium relevant degree: 6.3			
Béduwé et al. (2011)	France	D	-HM+not VM: -3.0 -HM+VM: -11.0 Controlled for job characteristics: -HM+ not VM: n.e. -HM+ VM: -7.0	-HM+ not VM: + -HM+VM: +	-HM+not VM:- -HM+VM:-	
Bender et al. (2011)	United States	B	Early career (<10 years since degree): -Partly/very HM: -1.9/n.e. -Very HM: -6.9/-7.7 Late career (>25 years since degree): -Partly/very HM: -4.5/-11.5 -Very HM: -21.1/n.e.			
Kucel et al. (2013)	Spain and The Netherlands	A				-Netherlands: + -Spain:+
Bender et al. (2013)	United States	B	Ref. cat.=wage/salary matched employees Wage/salary employees : -Moderately HM: n.e. -Severely HM: -21.1/-15.9 Self-employed: -Moderately HM: -8.8/-17.1 -Severely HM: -42.8/-33.0		Wage/salary employees: -Moderately HM:-/- -Severely HM:-/- Self-employed: -Moderately HM:-/- -Severely HM:-/-	
Zhu (2014)	China	B	-1.17/-1.45			
Shevchuk et al. (2015)	Russia	B	-Overall: -/- Controlled for caregiving (CA): -HM+CA: n.e./- -HM+not CA: -/-	-Overall: n.e. Controlled for caregiving (CA): -HM+CA: n.e./+ -HM+not CA: n.e.	-Overall: n.e./- Controlled for caregiving (CA): -HM+CA: -/- -HM+not CA: n.e./-	

Note: HM indicates horizontal mismatch, VM indicates vertical mismatch, + indicates a positive relation between HM and the outcome variable, – indicates a negative relation and n.e. indicates no effect. a. Definition of horizontal mismatch: A. based on self-report on whether a specific field of education was required for the job B. based on respondents' assessment of the extent to which their current occupation is related to their attended field of education C. respondents' assessment of whether or not they have been trained for their current employment D. objective measure. b. The 13 countries comprise Austria, Belgium, Denmark, Spain, Finland, France, Greece, Hungary, Italy, Luxembourg, The Netherlands, Sweden and Slovenia.

4. Discussion

Relying on a systematic literature review, the aim of this paper is to address how prevalent horizontal mismatch is and to what extent it contributes to an inefficiently functioning labour market. In addition, we discussed the approaches in which the concept of horizontal mismatch has been operationalized in prior research and identified the factors that determine horizontal mismatch.

Several specifications of horizontal mismatch can be found in the literature, each yielding different incidence rates. The highest incidence rates are proposed by studies using an objective definition (e.g, Béduwé & Giret, 2011; Malamud, 2011). On average, the different specifications generate incidence rates varying from 21 percent to 46 percent. The degree to which horizontal mismatch can be considered an undesirable phenomenon differs across mismatched individuals and depends among other things on the reason for accepting horizontal mismatch as well as on the degree to which skills are being underutilized. The reason for accepting a job that does not require employees' attended field of study may be demand as well as supply-related (Robst, 2007b). The source of horizontal mismatch is considered to be demand-related when a matching job is unavailable. Under this condition, horizontal mismatch can be considered a negative phenomenon given that students choose a field of study with the expectation of finding employment in field-related occupations (Betts, 1996; Holland, 1985). In fact, our review points out that horizontal mismatch often has unfavourable effects on employees' earnings, occupational status, and job satisfaction (e.g., Bender & Roche, 2013; Van de Werfhorst, 2002; Wolbers, 2003). Horizontal mismatch also increases the likelihood of experiencing programme regret which is associated with substantial costs (Authors, 2016; Borghans & Golsteyn, 2005; Kucel & Vilalta-Bufì, 2013). From this perspective, horizontal mismatch may reveal that the process of skill formation and the allocation of skills on the labour market are sub-optimal.

The negative consequences induced by horizontal mismatch are more ambiguous, however, when the source of mismatch is supply-related. Supply-related reasons for accepting horizontal mismatch may pertain to pay and promotion opportunities, or a change in career interests (Bender & Heywood, 2011; Robst, 2007a; Robst, 2007b). The majority of these employees receive a wage premium over their well-matched counterparts, suggesting that horizontal mismatch does not necessarily indicate a severe underutilization of field-specific skills (Robst, 2007a; Zhu, 2014). Other employees might accept horizontal mismatch in exchange for favourable job attributes such as a permanent contract or a greater flexibility in working hours (Béduwé & Giret, 2011; Benz & Frey, 2008; Connelly, 1992). Hence, from an

individual's perspective, accepting horizontal mismatch might be an economically rational decision under certain conditions. This also applies to employees in later stages of their career, especially in the presence of technological progress which induces skill obsolescence and the rise of new skill requirements (Bender & Heywood, 2011; Witte & Kalleberg, 1995). In fields that are sensitive to rapid changes, a greater value is being put on the skills acquired through work experience and on-the-job training. Whilst, from an individual's view, accepting mismatch can be economically rational, horizontal mismatch might still reflect an economic loss to society. This is the case when individuals' productivity level would be superior if a matching job or a different field of study would have been chosen. Whether horizontal mismatch in later career stages implies a labour market failure depends on whether employees gain new skills on the job and whether educational institutions adjust their curricula to meet changes in labour market demands.

This review proposes that future research could benefit from a more uniform measure of horizontal mismatch. Besides the fact that each definition of horizontal mismatch yields varying incidence rates, the validity of the different measures that are identified in the literature can be called into question. Although individuals might be employed in similar jobs and acquired the same field degree, there might still be a discrepancy in the degree to which employees perceive the match between their job and their attended field of study. Moreover, defining employees as being poorly matched because their field degree was not a requirement for their job might also give problems of validity. Where some jobs only accept individuals who have acquired a specific degree, other jobs require a set of skills that is being offered by a wider range of fields.

The current state of academic research also suffers from the absence of information and data about skills. Most studies included in this review consider educational requirements as a proxy for the knowledge and skills that are necessary to adequately perform the job. However, the knowledge and skills that are used in jobs only partially overlap with what is being taught throughout formal education. Hence, using education as a proxy for skills might ignore other important attributes of job requirements such as on-the-job training and job experience. Nonetheless, in a context in which public education is expected to provide students with the skills that are demanded on the labour market, formal degrees can be considered a good proxy for the skills that jobs require from recent graduates with little work experience. Hence, measuring the education-job fit in terms of the attended field is more informative about the transition from recent graduates to the labour market than about the extent to which older

employees possess the skills that are required for the job. Future research on skill mismatches could therefore benefit from the availability of data on the knowledge and skills required for jobs.

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Appendix A: Overview of the selected studies

	Author (year of pub.)	Country of study	Data source, type of data and year of data collection	Sample population	Statistical method	Determinants of horizontal mismatch subject to examination	Effects of horizontal mismatch subject to examination
1	Witte & Kalleberg (1995)	Germany	German Socioeconomic Panel (GSOEP) - cross-sectional - 1984–1990[a]	Representative household panel (final sample for models of mismatch determinants: men: n = 1,008; women: n = 637. Final sample for models of mismatch effects: men: n = 1,881; women: n = 1,207).	-Logistic regression to examine determinants -OLS regression to examine effects	-Type of vocational education -Opportunity structure -Job tenure -Occupational group -Firm size -Occupation 'cultures of training' -Gender -Age	Wage
2	Allen & van der Velden (2001)	The Netherlands	Data were collected for the project 'Higher Education and Graduate Employment in Europe' - cross-sectional - 1998	Tertiary education graduates who graduated in 1990/1991 and held a job of at least 12 hours per week at the time of the survey (final sample: n = 2,460).	-OLS: wage effects -Logistic regression: effect on on-the-job search and job satisfaction		-Wage -On-the-job search -Job satisfaction
3	van de Werfhorst (2002)	The Netherlands	Survey from The Netherlands Institute for Social Research (SCP) - time series - 1991,1995	Employed individuals aged 21–64 years with a minimum of 15 working hours per week (final sample: n = 6,373).	OLS regression: wage effects		Wage
4	Wolbers (2003)	Austria, Belgium, Denmark, Spain, Finland, France, Greece, Hungary, Italy, Luxembourg, The Netherlands, Sweden and Slovenia.	2000 ad hoc module of the European Labour Force Survey (EU LFS 2000) - cross-sectional - 2000	Individuals aged 15–35 years who left formal education within the past five years (Finland, Luxembourg, the Netherlands and Sweden) or ten years (all other countries) years (final sample: n = 36,268).	-Logistic regression to examine determinants -Logistic regression: effects	-Field of study -Level of education -Type of vocational education -State of the economy -Job tenure -Type of contract -Firm size -Sector -Gender -Age	-On-the-job search -Training participation -Occupational status

5	Robst (2007a)	United States	National Survey of College Graduates (NSCG) from the National Science Foundation- cross sectional - 1993	Nationally representative sample of individuals in the United States who indicated on the 1990 Census to have attained at least a bachelor's degree (final sample: n = 124,063).	-Ordered logit regression: determinants -OLS regression: effects	-Field of study -Level of education -Gender -Age -Ethnicity -Having a disability -Marital status	Wage
6	Robst (2007b)	United States	National Survey of College Graduates (NSCG) from the National Science Foundation- cross sectional - 1993	Nationally representative sample of individuals in the United States who have attained at least a bachelor's degree (final sample: n = 124,063).	-Logit regression: determinants -OLS regression: effects	*Robst (2007b) uses the same dataset and includes the same regressors. Footnotes in the text report when different coefficients were obtained for these variables.*	Wage
7	Hensen et al. (2009)	The Netherlands	Two surveys from the Research Centre for Education and the Labour Market (ROA): Registration of Outflow and Destination of Graduates (RUBS) and HBO-monitor - time series - 1996–2001	Individuals aged 16-30 years, surveyed 18 months after graduation, who attended full-time pre-secondary vocational, secondary vocational or higher vocational education. The individuals are in paid employment (final sample: n = 83,239).	Logistic regression: determinants	-Field of study -Level of education -State of the economy -Job density* -Gender -Age -Ethnicity -Job mobility	
8	Cosser (2010)	South Africa	Research Programme on Human Resources Development (HRD) - time series - 2001, 2002,2006	(Final sample: 496,120).	Descriptive analysis		
9	Malamud (2010)	England and Scotland	Survey conducted by the British Department of Employment: 1980 National Survey of Graduates and Diplomates (NSGD) - cross sectional – 1986/1987	Scottish and English university graduates who obtained their BA degree in 1980. Individuals were employed full-time in the first year after graduation (final sample NSGD: n = ± 4,800).	OLS regression: effects	*Malamud (2011) uses the same dataset and also examines the effect of the timing of academic specialization on horizontal mismatch. Results were similar.*	-Wage -Annual earnings growth* -On-the-job search - Getting an interesting job
10	Mora (2010)	Spain	The Quality Assurance Agency for seven public universities in Catalonia - cross-sectional – 2000	1997/98 graduates aged 23–33 years from a public Catalan university (final sample n > 3500)	Probit- and two-step probit regressions with endogenous regressor		Study programme regret

11	Nordin, et al. (2010)	Sweden	Data from Statistics Sweden (SCB): education data of Swedish Register of Education (UREG) and income data of National Tax Board were added to register of the total population (RTB) - cross-sectional - 2003	Swedish-born individuals aged 28–39, with a college /university degree (final sample men: n = 67,607; final sample females: n = 116,750)	OLS regression: wage effects		Wage
12	Yakusheva (2010)	United States	Survey conducted by the U.S. department of education: High School and Beyond (HS&B) - longitudinal 1982,1984,1986,1992	Sample of 1980 high school sophomores with some post-secondary education (4 years at most) (final sample: n = 2,268).	OLS regression: wage effects		Wage
13	Béduwé & Giret (2011)	France	Generation 98 survey - cross-sectional - 2001	Graduates from secondary vocational educ. and first level of higher education, 3 years after graduation (final sample: n = 21,780).	-OLS regression: wage effects -Probit regression: effect on on-the-job search and job satisfaction		-Wage -On-the-job search -Job satisfaction
14	Bender & Heywood (2011)	United States	Survey of Doctorate Recipients (SDR) - panel - 1993,1995, 1997,1999,2001,2003 and 2006	PhD graduates in a (hard or social) science, math, or engineering (SME) field and who reside in the United States (final sample > 200,000).	-Descriptive analysis: determinants -Fixed effects regression: effects	-Field of study -Sector -Gender -Age -Disability -Naturalized citizen* -Noncitizen vs. noncitizen*	Wage
15	Farooq (2011)	Pakistan	Survey of Employed Graduates (SEG) and Labour Force Survey (LFS) - time series - 2010 (SEG) and 2006/2007, 2008/2009 (LFS)	Employed graduates working in the formal sector with a Bachelor's, Master's or doctoral degree. (final sample: n = 513).	Logistic regression: determinants	-Field of study -Level of education -Time devoted to studies -Occupational group -Gender -Socioeconomic background * -Annual vs. semester system*	
16	Malamud (2011)	England and Scotland	1980 National Survey of Graduates and Diplomates (NSGD) conducted by the British Department of Employment and	NSGD: 1980 graduates from Scottish and English universities USR: administrative data on all students in British universities and Scottish	OLS and two stage least squares regression: determinants	Timing of academic specialization	

			Universities Statistical Record (USR) - cross-section - 1986/1987 (NSGD), 1972–1993 (focus on 1980) (USR)	universities (final sample: n = 15,337).			
17	Boudarbat & Chernoff (2012)	Canada	Follow up of Canadian Graduates - Class of 2000 survey - cross-section - 2005	University graduates (Bachelor and beyond), 5 years after graduation (final sample: n = 9,335)	Logit regression: determinants	-Field of study -Level of education -Activities before university -Time devoted to studies -Type of contract -Method to obtain job -Gender -Age -Ethnicity -Parental education -Ability (grades) -Family wealth*	
18	Kucel & Vilalta-Bufí (2012)	Poland	HEGESCO survey for Poland - cross-section - 2008	Graduates who received their bachelor's or master's degree (ISCED5A) in 2002/2003. Self-employed and part-time employees are excluded. (final sample: n = 692)	Logistic regression: determinants	-Field of study -Level of education -Vocational education -Internship during studies -Prestige of university -Employers' familiarity with programme -Difficulty study programme* -Freedom to compose study programme* -Broadness study programme* -Job tenure -Firm size -Gender -Age -Ability (grades) -Possessed competencies*	
19	Bender & Roche (2013)	United States	Dataset from the US National Science Foundation (NSF): National Survey of College Graduates (NSCG) - cross-section - 2003	Employees with at least a bachelor's degree in a hard or social science, technology, engineering, or mathematics (STEM) field (final sample: n = 74,229)	-Ordered probit: determinants -OLS: wage effects -Ordered probit: effect on job satisfaction	-Level of education -Occupational group -Gender -Age -Ethnicity -Marital status -US citizenship*	-Wage -Job satisfaction

20	Kucel & Vilalta-Bufí (2013)	Spain and Netherlands	REFLEX survey data - cross-section - 2005	1999/2000 Tertiary graduates (final sample Spain: n = 2,777; Netherlands: n = 2,683)	Logistic regression: effect on study programme regret		Study programme regret
21	Levels et al. (2014)	20 countries[b]	European Union Labour Force Survey 2009 Ad Hoc Module (EU LFS 2009) - cross-sectional - 2009	Individuals aged 15–34 years with upper-secondary and post-secondary education who graduated between 1989–2009. (final sample: n = 30,805)	Multi-level logistic regression: determinants	-Vocational education -Vocational orientation education system -Strength institutional linkages -Standardization of curricula and outcomes*	
22	Robert (2014)	Hungary, Poland, Lithuania and Slovenia	HEGESCO survey, follow-up of REFLEX project (same questionnaire)– cross-sectional - 2008/2009	Individuals who graduated five years before in 2002/2003 (final sample: n = 6,665)	Logistic regression: determinants	-Field of study -Work experience during educ. -Job search duration -Type of contract -Gender -Age -Job mobility -Parental education	
23	Zhu (2014)	China	2008 Chinese College Graduates' Employment and Work Skills Survey - cross-sectional - 2008	2007 Graduates from 43 4-year colleges in the Shandong province 6–12 months before survey (final sample: n = 5,879)	OLS regression and nonparametric local linear kernel estimation: wage effects		Wage
24	Shevchuket al. (2015)	Russia	Online questionnaire conducted by the authors - cross-sectional data - 2011	Russian-language internet freelancers with a completed tertiary degree (final sample men: n = 918; women: n = 684)	-Ordered probit: effects on wage and job satisfaction -Logistic regression: effect on on-the-job search		-Wage -On-the-job search -Job satisfaction

Note: * indicates that this variable was examined by only one study and no significant effect was found. b. Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Finland, France, Greece, Hungary, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Sweden, Slovenia, Slovak Republic and the U.K a. Wave 1987 is used to estimate the incidence and determinants of horizontal match. As a robustness check, cross-sectional logistic regressions were estimated separately for each year from 1984 to 1990. The estimated coefficients were consistent over the years. The wage regressions were estimated on the monthly gross earnings of 1984.

Appendix B: Strategy used in computerized databases search

ERIC [DECEMBER 2015]

- Keywords: “fit OR match OR mismatch” AND “college OR education OR major OR program OR study” AND “employment OR job OR labor OR labour OR occupation OR work” AND “field” +pubyear:1995
- Limit results to “ Peer reviewed only”

EBSCOhost EconLit [DECEMBER 2015]

- Keyword: “fit OR match OR mismatch” AND “college OR education OR major OR program OR study” AND “employment OR job OR labor OR labour OR occupation OR work” AND “field”
- Limit to: “January 1995” to “December 2015” within “Select a Field (optional) ”
- Source types: “Academic Journals”
- Language: “English”

EBSCOhost SocINDEX [DECEMBER 2015]

- Keyword: “fit OR match OR mismatch” AND “college OR education OR major OR program OR study” AND “employment OR job OR labor OR labour OR occupation OR work” AND “field” within “Select a Field (optional)”
- Limit to: “Scholarly (Peer Reviewed) Journals’, “January 1995” to “December 2015”
- Language: “English”

Is Job Turnover the Answer to Recession?

Sofie Cabus; Chris van Klaveren; Ilja Cornelisz

Abstract

Job turnover can mitigate some of the consequences of a recession under the condition that the labour market is able to allocate workers to jobs efficiently; the allocation of workers to jobs yields better fits in terms of education; and speed of job turnover should exhibit a countercyclical pattern. This hypothesis is tested for one Euro Area country, the Netherlands. We indicate that this country did not experience a shift in the UV-curve, partly owing to the employability of skills of the high-educated across sectors, and partly owing to the relatively high allocative efficiency of the Dutch labour market.

Keywords: Education; Job Turnover; Job Openings; Labour Market Sector; Unemployment

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1. Introduction

This study examines the macro-level and micro-level relationship between unemployment and unfilled job openings in the wake of the financial crisis and the Great Recession for one European Union country (the Netherlands). This relationship often has been referred to as the Beveridge- or UV-curve (Blanchard et al., 1989). In particular, sectoral mismatch between job-seekers and vacancies can shift the Beveridge curve to the right as an increasing number of unemployed persons cannot easily transfer to other sectors (or industries, or occupations) to get a new job (among others, Star-McCluer, 1993; Şahin et al., 2014; Daly et al., 2011, 2012; Barnichon et al., 2012; Davis et al., 2012; Cappelli, 2014). As a result of sectoral mismatch, high unemployment rates go together with a substantial amount of unfilled vacancies, and, in the long-run, can even establish a new, higher structural (natural) unemployment rate (Lazaer and Spletzer, 2012). This empirical finding has been observed for the Euro-Area and the United States of America over the past two decades (Statistical Office of the EU (Eurostat, 2016); US Bureau of labour statistics, 2016). However, the Beveridge curve for the Netherlands did *not* shift outward between 2005 and 2016, despite having experienced a similar economic downturn (Erken et al., 2014; Section 3).

One potential explanation is that sectoral mismatch is a less important issue in the Netherlands. Evidence for this hypothesis implies that job turnover across sectors did not decline in response to a prolonged period of economic downturn. Instead, job turnover can inhibit the negative effects of shifts in reallocation intensity on the aggregate economy by improving the allocative efficiency of labour, and, consequently, should exhibit a countercyclical pattern (Daly et al., 2011, 2012). In this study, we examine the pattern of sector-specific job turnover in two years of recession 2012 and 2013. Furthermore, we examine the 'quality' of the job turnover in terms of a better fit between the education supplied by the worker and the education demanded by the employer in the new job compared to the previous job. We also analyze whether the high-educated are substitutes or complements for the low-educated. As such, for the empirical analyses, we combine macro-level (Section 3) and micro-level analyses (Section 4). At the macro-level, we rely on administrative aggregated data of Statistics Netherlands. The macro-level analyses are mainly descriptive in nature and aim at positioning the Netherlands among other countries of the Euro Area, while, at the same time, identifying trends on the Dutch labour market between 2005 and 2016. At the micro-level, we merge unique micro-level longitudinal administrative data on unemployment, occupational, and educational background of *all*

persons in the Netherlands with information on unfilled job openings. Then, we estimate competing risk survival models in order to retrieve the likelihood of job turnover to others sectors and by (required) education attainment.

Hereby, this paper contributes to the previous literature on the relationship between unemployment and unfilled job openings in at least three ways. First, microeconomic analyses of the relationship between sectoral mismatch and shifts in the UV-curve almost solely have been done for the US, while, in fact, the Great Recession had impact on most OECD countries (Ball, 2014). We analyze the microeconomic relationship between unemployment and vacancies for the Netherlands. With its high employment protection policy (relative to the US), and good social security system in terms of a well-established unemployment insurance (oecd.org/employment, 2016), the Dutch labour market offers a different context than the US.[7] Furthermore, the Netherlands did not experience an outward shift in the Beveridge curve like most other Euro Area countries (Section 3), which makes the country an interesting case study.

Second, practically all US-economists use the Job Openings and Labour Turnover Survey (JOLTS) for estimation of the "rate of unfilled job openings", and the Current Population Survey (CPS) for information on unemployment rates, in order to construct the Beveridge curve. JOLTS consists of information on job openings, hires, layoffs and quits, while CPS is a monthly survey financed by the Bureau of Labour Statistics. Barnichon et al. (2012) discuss that studies using these data have substantial limitations. For example, only in one study, JOLTS has been used in combination with Help Wanted OnLine (HWOL) in order to classify vacancies by education attainment (Şahin et al., 2014). Our study combines unique micro-level administrative data on unemployment, occupational, and educational background of *all* persons in the Netherlands with daily information on unfilled job openings. This allows us to discuss trends on unemployment and job turnover across sectors and by education attainment.

Third, we analyze whether low-educated workers in the labour market are increasingly crowded out by high-educated workers in times of recession. It is argued in the previous literature that persons are more willing to accept jobs requiring a lower (than their own) level of education in poor economic situations (see, among others, Teulings and Koopmanschap, 1989; van Ours and Ridder, 1995; Dolado et

[7] Already in the 1990s, Mortensen and Pissarides (1999) argued in their work that countries with high employment protection, in combination with high unemployment insurance, yield higher (natural) unemployment rates relative to those countries who do not (or only limited) have these strict policies. As a result, 'bad shocks' on the labour market increase the unemployment rate the most in countries with elabourated employment protection and unemployment insurance policies.

al., 2000). This may lead to a situation wherein high-educated workers are increasingly vertically mismatched to jobs, while, at the same time, relatively high unemployment rates will arise among the low-educated. To the best of our knowledge, this has not been done in other studies dealing with mismatch during the Great Recession due to previously discussed data limitations (see also Section 2).

This paper proceeds as follows. We discuss the previous literature with particular focus on mismatch in Section 2. In Section 3, we sketch the situation for the Netherlands by plotting the Beveridge curve and discussing the hypothesis of mismatch (across sectors and by education attainment). Section 4 elabourates on the estimation method. The data are discussed in Section 5, and the results in Section 6. Section 7 concludes.

2. Impact of great recession

The US literature dealing with the impact of the Great Recession outlines four hypotheses that are in line with a (temporary) shift (to the right) of the Beveridge curve (information can be retrieved from, among others, Şahin et al., 2014; Daly et al., 2011, 2012; Barnichon et al., 2012; Davis et al., 2012; Cappelli, 2014): (1) sectoral (or occupation, or industry) skill mismatch between job-seekers and vacancies structurally shift the Beveridge curve to the right; (2) reduced recruiting intensity causes a shortfall in vacancy yield; (3) extension of unemployment insurance benefits declines job search intensity of unemployed persons, and reduces job offers acceptance by unemployed persons; and (4) the value of marginal productivity of workers increased, so that fewer workers are necessary to produce the same output. This paper solely focusses on the first hypothesis dealing with sectoral mismatch.

In the previous literature, shifts in reallocation intensity often have been associated with the rise of mismatch on the labour market (Blanchard et al., 1989). Shifts in reallocation intensity may happen as a result of changes in the production function, which, in turn, changes the demand for labour. For example, owing to innovations a firm can substitute away from low-skilled labour to high-skilled labour. Already in mid-1900s, Schumpeter (1942) wrote how innovations could lead to the destruction of jobs, while, at the same time, creating new jobs (often referred to as 'Creative Destruction'). Shifts in reallocation intensity owing to innovations do not affect aggregate employment *unless* matching workers to jobs is not instantaneous. Therefore, innovations may imply a transition period wherein workers, who lost their jobs, search for a new match on the labour market. Mismatches on the labour market then arise when the skills of unemployed job seekers do not fit the new methods of production.

Hereby, it is acknowledged that the labour force is a heterogeneous pool of workers and that labour demand is not uniform. For example, geographic locations with high rates of job creation for high-skilled workers may suffer from low-availability of those high-skilled workers. This leads to high(er) levels of unemployment (than before), even though the substantial amount of vacancies (for the 'new' jobs).

In times of recession, however, it is not (or unlikely) innovation in production technology that may impact mismatch between job-seekers and vacancies, but the necessity of workers to switch between sectors in order to find a new job (Star-McCluer, 1993). However, Hershbein and Kahn (2016) provide recent evidence that recessions can accelerate routine-based technological change. This implies that firms invest in innovations in production technology in order to substitute away from expensive routine-labour tasks. Increases in physical capital are mostly in favor of high-skilled labour, reducing, again, employment opportunities for the low-skilled on the labour market. For those workers with sector, occupation or industry specific skills, the switch between sectors in order to find a new job is not an easy transfer, in particular, when they need to transfer to a sector requiring different sector, occupation or industry specific skills. Mismatch then arise for workers who acquired skills in the past that do not meet production technology of the new sector of employment. It is clear that an increase in the prevalence of mismatch, indicating the lack of skills to meet the (new) production technology of the firm (within or) across sectors leads to a structural upward shift in the unemployment rate (i.e. it impacts the natural unemployment rate).

However, evidence indicates that labour market mismatch is limited in explaining rising unemployment rates during the Great Recession (Daly et al., 2012). For example, Barnichon et al. (2012) argue that the degree of industry mismatch increased at onset of the Great Recession, and then again decreased to levels only slightly higher than before 2008. Furthermore, Daly et al. (2011) argue that high degrees of mismatch should go along with high job turnover rates in particular industries, whereas employers make job offers to employed workers in other firms in order to fill their own vacancies. There is no evidence of such elevated quit rates in the US. On the contrary, Hobijn and Sahin (2013) find a decline in quits in the US.

Cappelli (2014) confirms that mismatch is not an issue in the US. The author argues that there is no evidence of 'skill gaps' or 'skill shortages', but rather 'excess skills', as job applicants often have more skills than required for the job task. However, he also argues that learning relevant or appropriate skills (for the job) have become increasingly a responsibility of job seekers and schools, whereas in the past it was the employer who invested in the skills of apprentices. This shift in responsibility away from

employers and towards job seekers and schools may be related to reducing labour costs. It also implies that families and students take the financial risk of investment in their skills. Consequently, students search for employment in industries that yield highest return on their investment in skills. Some industries, like manufacturing, therefore, suffer from recruiting bottlenecks. Wages in this industry declined with about 20 percent, and the skills necessary for working in this industry shifted from labour-intensive to computer-based. But students who have strong computer skills are generally well-educated and attracted to industries that yield higher returns to education.

Şahin et al. (2014) have explored whether mismatch between skill demand and skill supply can explain why the unemployment rate did not fall (when the US economy recovered in 2010). Therefore, they estimate the gap between optimal (or efficient) allocation of workers to jobs and factual allocation. This yields a mismatch index. Optimal allocation can then be considered the (unobserved) counterfactual outcome of sub-optimal allocation due to mismatch. In order to retrieve the optimal labour market outcomes of workers, Sahin and co-authors build an impressive theoretical model for empirical application. Model estimations account for different types of mismatch (across industries, occupations, or geographical locations), and also account for heterogeneity of mismatch across education attainment. It is concluded from their work that mismatch across industries and occupations accounts for 0.8 to 1.4 percentage points of the total 5.4 percentage points increase in the unemployment rate over the period 2007-2009. These estimates are mainly driven by high-skilled workers. Moreover, they do not find evidence of geographical mismatch.

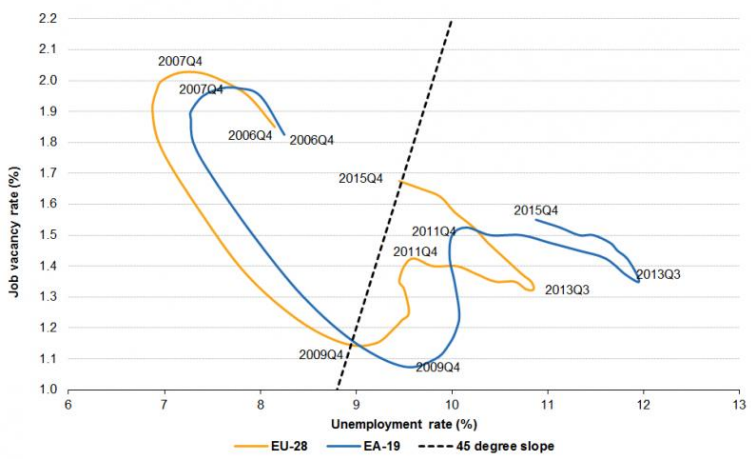
3. Empirics: analysis at macro-level

3.1. International evidence

The point of departure for the macro-level analysis is plotting the Beveridge curve for EU-28 countries and the Euro Area (EA-19) on Figure 1. We observe that, as a result of the financial crisis, the total number of unfilled job openings dropped from above 2.0 percent in 2007Q4 to nearly 1.1 percent in 2009Q4, while, at the same time, unemployed increased rapidly in 2008-09. After 2009Q4, one can observe an outward shift of the UV-curve for EU-28 Member States and the Euro Area. When only looking at the 19 countries of the Euro Area, the outward shift of the UV-curve is more pronounced. However, the figure masks great disparities between Member States (for a discussion see Bonthuis et al., 2013). This is clearly visualized on Figure 2. The plot presents a snapshot of the average UV-curve for

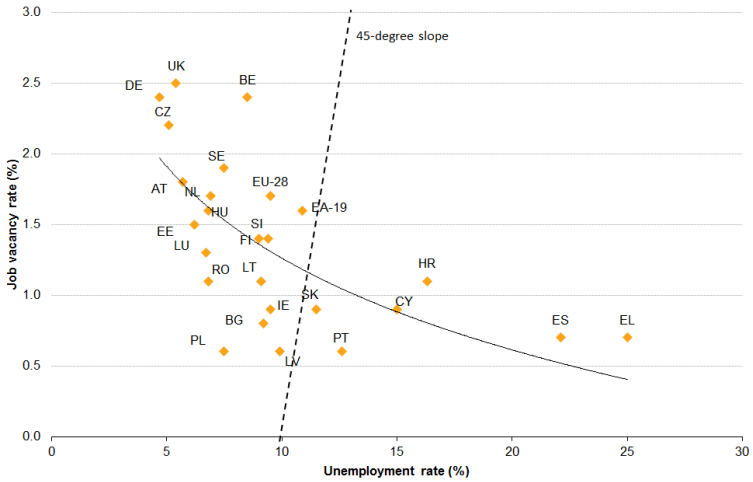
the year 2015. The 45-degree line denotes whether a country suffers from economic recession (then, situated below the line) or benefits from economic revival (then, situated above the line). For every Member State in EU-28 (excl. Denmark, France, Italy, Malta), there is a "Beveridge point" on, below, or above the UV-curve. Each Beveridge point reflects the efficiency of matching job-seekers to vacancies. For example, on the one hand the United Kingdom (UK) has a job vacancy rate of 2.5 percent and an unemployment rate of about 5 percent. On the other hand, Portugal (PT) has a job vacancy rate of nearly 0.5 percent and an unemployment rate of about 13 percent. The Beveridge point of the UK lies far above the UV-curve, indicating that the matching efficiency of the UK is rather poor compared to other countries below the UK and closer to the UV-curve. The Beveridge point of PT lies below the UV-curve, indicating that the high level of unemployment in this country is due to low job creation (or high job destruction), so that there are too few employment opportunities for the unemployed to find a job (that matches their skills). In such a country the efficient matching of job-seekers to vacancies is also far from optimal. As such, (relative) matching efficiency is highest on the UV-curve. Austria, Cyprus, Hungary, Finland and the Netherlands are lying close to the UV-curve.

Figure 1: The Beveridge curve for EU-28 countries and the Euro Area (EA-19), 2006Q4-2015Q4



Source: http://ec.europa.eu/eurostat/statistics-explained/index.php/File:Figure1_Bev_curve.PNG

Figure 2: Cross-country Beveridge points for EU-28 countries and the Euro Area (EA-19), average of 2015Q1-2015Q4

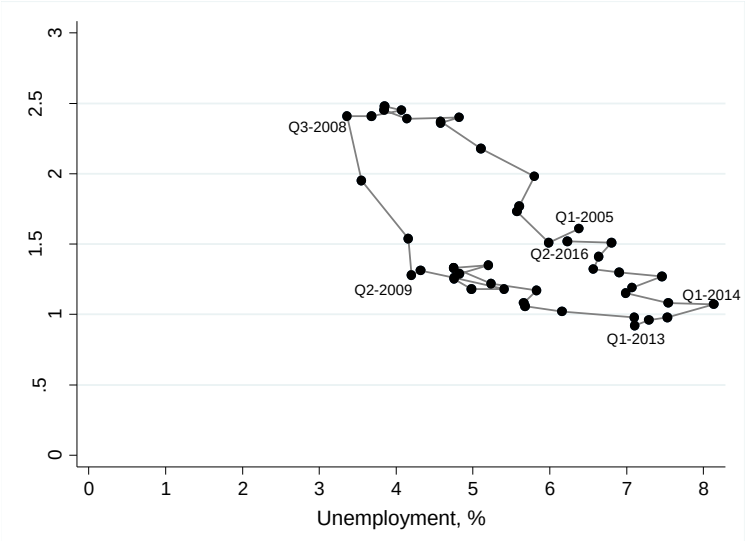


Source: http://ec.europa.eu/eurostat/statistics-explained/images/0/0a/Figure2_Bev_points.PNG
Note: Denmark, France, Italy and Malta are not included because of incomplete measurement of unfilled job vacancies.

3.2. Beveridge curve for the Netherlands

The Beveridge curve for the Netherlands is plotted on Figure 3. The underlying macro-level data are available at Statistics Netherlands (cbs.nl) and are summarized in Appendix A0. Between the third quarter of 2008 and the second quarter of 2009, the total number of unfilled job openings declined substantially from almost 2.5 percent to nearly 1 percent. After this huge drop in the rates of unfilled job openings, unemployment rates rapidly increased from 4 percent in 2009 to almost 8 percent in the first quarter of 2014, while the rates of unfilled job openings remained fairly stable at 1 percent. At the time being, many people believed that observed movements on the UV-curve had established a new, higher natural unemployment rate. Today, it is observed that unemployment rates are slowly moving down again, and this in combination with increasing rates of unfilled job openings. The second quarter of 2016 even holds the promise that unemployment will further decline to the levels observed before 2008. From this evidence we can conclude that the Beveridge curve for the Netherlands did not shift outward. However, the years of recession 2012-2013 are still interesting for further analysis in order to understand why the Netherlands did not establish a 'new normal' (cf. Lazaer and Spletzer, 2012) and compared to other countries in the Euro Area.

Figure 3: The Beveridge curve for the Netherlands, 2005Q1-2016Q2



Source: Own calculations based on Statistics Netherlands.

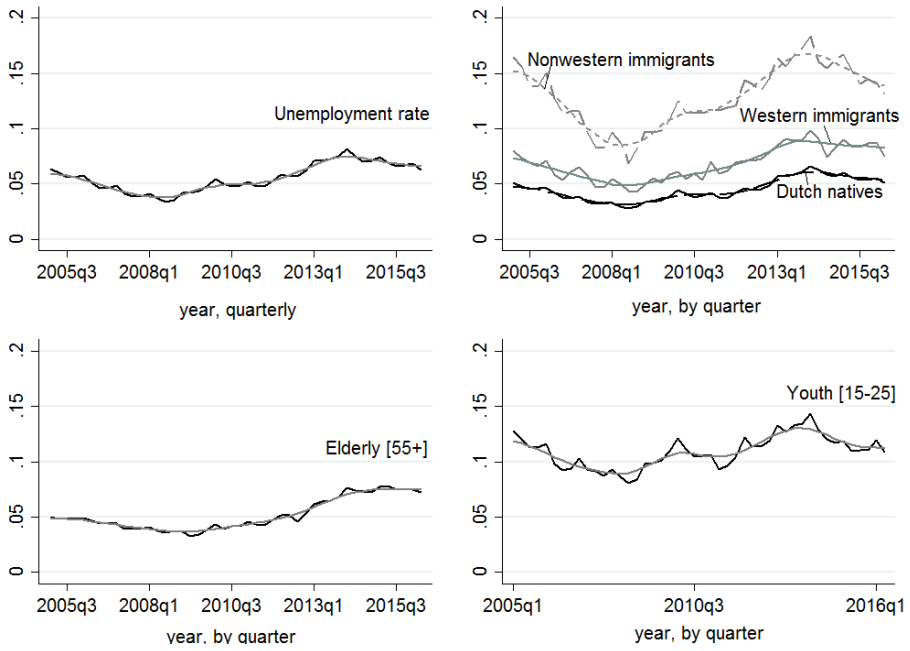
3.3. Labour force participation and unemployment trends

Figure 4 presents the evolution of labour force participation rates (left panel) and unemployment rates (right panel) over the period 2005-2015. Normally, labour force participation rates and unemployment rates move in opposite directions. When the unemployment rates go up because of a slack economy, people tend to wait in unemployment for better times on the labour market (cf. the discouraged worker effect, Lundberg, 1985; Benati, 2001; among others). This can be observed between 2005 and 2011. However, the years 2012 and 2013 present a parallel movement of the labour force participation rates and the unemployment rates. As such, people increasingly participated in the labour force in times of high unemployment (cf. the added worker effect, Lundberg, 1985; Stephens, 2002; among others). In order to understand why this happened in particular in these two years of recession, we decompose the unemployment rates by demographic characteristics (Figure 5) and by education attainment (Figure 6). From Figure 5, it is observed that non-western immigrants and young people aged 15-25 are disproportionally driving up the unemployment rates. Furthermore, from figure 6 we retain that people with relatively low education attainment (ISCED1-ISCED3) have highest risks on (increasing) unemployment.

Figure 4: Evolution of the labour force participation rates (left panel) and unemployment rates (right panel), Netherlands

Source: Own calculations based on Statistics Netherlands.

Figure 5: The unemployment rate (x100, %) by total labour force (1); origin (2); older people (3); and youth (4)

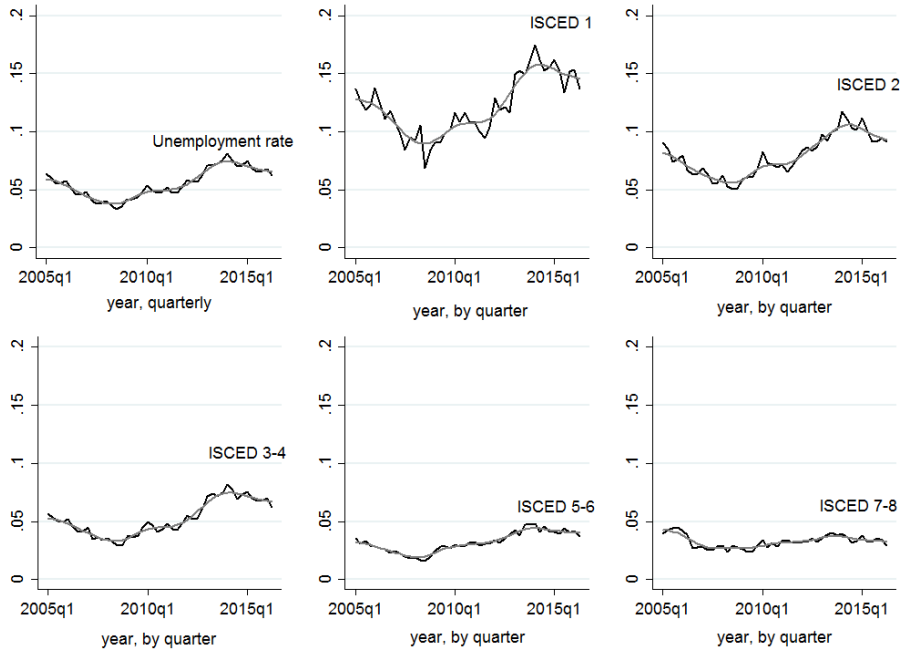


Source: Own calculations based on Statistics Netherlands.

Next, we decompose labour force participation by age groups and education attainment. According to the Dutch Employee Insurance Agency (UWV), the observed increase in labour force participation over the period 2012 and 2013 is driven by young graduates and older workers. Figure 7 plots labour force participation (employment in thousands) among young [15-25] and older [55-65] workers and by

education attainment. From these plots, a sharp rise in labour force participation is particularly observed among older workers with ISCED 3-4 between 2013Q1 and 2014Q1. Furthermore, there is an overall positive trend since 2005 in labour force participation among older workers with an education attainment of ISCED 5-8. There is also an increasing trend in labour force participation among higher educated youngsters. However, the effects of the recession on labour force participation of the high-educated are far less pronounced than those observed for older workers. On the contrary, since the end of 2008, labour force participation decreased among older as well as younger workers with the lowest education attainment ISCED 1-2.

Figure 6: The unemployment rate (x100, %) by education attainment, ISCED

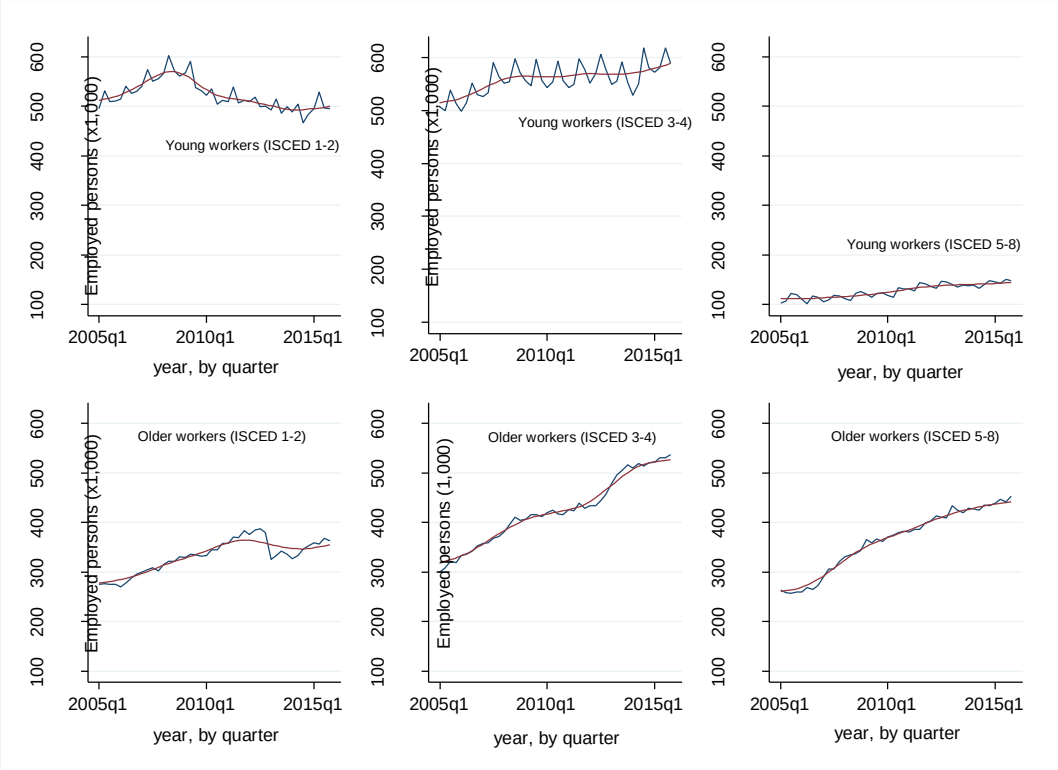


Source: Own calculations based on Statistics Netherlands.

We retain from the macro-level analysis that in the wake of the financial crisis and the Great Recession, the Beveridge curve for the Netherlands did not shift outward. This is in sharp contrast with the shift observed for the whole Euro Area. International evidence indicates an overall high efficiency of matching job-seekers to vacancies on the Dutch labour market. Furthermore, a sharp rise in employment has been observed in 2013 particularly among older workers with secondary education. The Dutch Employee Insurance Agency argues that older workers stay longer at work because of legislation changes in pension schemes, in particular, for the public sector in 2006, leading to insecurity about old age pension allowance. However, there is no causal evidence on this relationship, and

delivering this evidence is considered beyond the scope of this study.[8] Nonetheless, the analysis at micro-level will shed more light on job turnover flows, by analyzing individual unemployment spells.

Figure 7: Labour force participation among young and older workers (x1,000) by education attainment, ISCED



4. Empirics: analysis at micro-level

4.1. Sectoral mismatch and crowding-out

Whereas the Great Recession is associated with job destruction and high unemployment rates, economic recovery of such an historical event implies that unemployed workers find, again, new jobs. Labour mobility in general, and job turnover in particular, is a mechanism that ameliorates the matching of workers to new jobs. It is then the question whether workers, who face increasing competition on the labour market for new jobs in times of recession, are increasingly mismatched in these new jobs. If, the competitive labour market equilibrium is efficient, then there would be no reason to doubt that both

[8] Recently, Montizaan and Vendrik (2014) have estimated the effects of changes in the public pension scheme on older workers' job satisfaction and other measures of subjective well-being. They found a significant decline in job satisfaction due to the policy changes.

workers and firms are in their best or optimal match. However, the assumption of efficient labour market equilibrium is naïve. First of all, the literature on *sectoral mismatch* argues that individuals face sector-specific labour markets and, therefore, the corresponding labour market dynamics (see, among others, Jovanovic and Moffitt, 1990; Starr-McCluer, 1993). If labour markets are indeed sector-specific, this would imply that unemployed persons will (particularly) find jobs in the sector in which they were (last) employed before their period of unemployment. This holds particularly when workers' skills only meet sector-specific production technology and these skills are difficult to transfer across sector (e.g. this would require an investment in education or on-the-job training in the sector of new employment) (Acemoglu and Piscke, 1998; Leuven and Oosterbeek, 1999; Lazaer, 2009).[9] This labour market feature would substantially restrict labour mobility, in particular, for those unemployed individuals who are working in sectors that are hardly hit by the recession and that require a lot of sector-specific skills. Therefore, theory on sectoral mismatch argues that unemployment in times of recession may rise, not so much because total demand for labour in the economy is lower, but rather because it takes time for unemployed individuals, who actively search for jobs, to switch from a sector with no jobs to a sector with new jobs (Starr-McCluer, 1993). This would indicate a positive relationship between the intensity or duration of an economic recession and the intensity of labour mobility in terms of unemployed persons switching between sectors (Daly et al, 2011). Notably, proof of this relationship would indicate that sectoral mismatch is not structural but transitory in nature.

However, facing increased competition on the labour market, unemployed individuals may be more willing to accept jobs requiring a lower (than their own) level of education attainment in times of recession (see, among others, Teulings and Koopmanschap, 1989; van Ours and Ridder, 1995; Dolado et al., 2000).[10] When a person's own education attainment deviates from the required education attainment, this corresponds to vertical mismatch (Hartog, 2000; Groot and Maassen van den Brink, 2000). Vertical mismatch can be the result of a suboptimal allocation process wherein high-ability workers are matched to jobs that are, in fact, for less-able persons (at least, according to their education attainment). This corresponds to a situation in which high-ability workers are crowding out less-able workers on the labour market. It is unclear whether a proof of crowding out would indicate structural

[9] Skills that are sector-specific are also called 'job-specific-skills'. This is in contrast to 'general skills' which are easily transferable across sectors (Lazaer, 2009).

[10] The literature on mismatch by education attainment generally distinguishes between vertical mismatch and horizontal mismatch. Horizontal mismatch reflects the situation in which the acquired field of education does not match the type of job (Somers and Cabus, 2016). Due to empirical restrictions, this study focuses only on vertical mismatch. However, we do consider horizontal mismatch as an important scope for further research.

vertical mismatch, or cyclical. Previous literature indicates that over-education can be a trap (i.e. structural), in particular for youngsters at the start of the career (Baert et al., 2013).

In sum, the empirical micro-level results of this study focus on testing sectoral mismatch and crowing out (owing to vertical mismatch) by analyzing the following four questions: (1) Is the relationship between unemployment and unfilled job opening is sector-specific? (2) Do persons switch labour market sectors after a period of unemployment in times of recession? (3) Is the relationship between unemployment and job opening rates education-specific? And (4), are high-ability workers (increasingly) crowding out less-able workers on the labour market in times of recession? The estimation method is discussed next.

4.2. Estimation method

Daly et al. (2011) argue that job turnover increases (layoffs, quits, hiring) when it is difficult to find suitable workers for unfilled job openings. Increased job turnover in times of recession can be derived from the positive relationship between the intensity or duration of an economic recession and the intensity of labour mobility in terms of unemployed persons switching between sectors. In order to estimate this relationship, we use a competing risk survival model that estimates the likelihood of transition from unemployment to employment. We focus on unemployment spells as this vulnerable group is particularly relevant for analyzing labour market mobility constraints. Furthermore, statistics regarding unfilled job openings are particularly relevant for this group. Given the existence of unemployment insurance benefits, this group is also of particular interest from a policy perspective.

The transition probabilities estimated are, in fact, conditional probabilities, as different employment types are considered, and because the estimation model conditions on unemployment duration and individual background characteristics. The likelihood of transition to different types of jobs is generally referred to as the 'hazard rate' which is expressed as a ratio. Intuitively, this ratio reflects 'the risk' of transitioning from unemployment to a particular form of employment. The ratio equals 1 when the hazard rate is not elevated. Values significantly below (above) 1 denote reduced (increased) hazard rates.

In this study, we focus on sectoral transitions and account for potential heterogeneous hazard rates by levels of education attainment. The sector-specific transitions are estimated by: (1) transfer to job in the same sector (as before unemployment); (2) transfer to job in different sector (as before

unemployment); (3) transfer from/to job in unknown sector; and (4) transfer to different situation (e.g. social assistance, pension, inactive). The education-specific transitions are estimated by: (1) transfers to job in a branch with an on average *higher* level of education (than branch of job before unemployment); (2) transfers to job in a branch with an on average *similar* level of education (than branch of job before unemployment); (3) transfers to job in a branch with an on average *lower* level of education (than branch of job before unemployment); (4) transfers from/to unknown branch; and (5) transfers to different situation (e.g. social assistance, pension, inactive).[11]

Below we do not specifically refer to education or sector specific transitions, but simply assume that there are *w* transitions to consider. The probability of observing a transition to one of the three employment types (*hazard rate*) can be denoted as:

$$\lambda_w(t \mid X) = \lambda_0 w(t) \cdot exp(X'\beta_w + \alpha_w), \quad (1)$$

where $\lambda_w(t \mid X)$ denotes the baseline hazard function for transition w; and X a vector of background characteristics. Parameters β_w and α_w are the parameters to be estimated, and for this purpose a semi-parametric Cox-model is used with a flexible baseline hazard function. The cumulative incidence function, denoted by $F_w(t \mid X)$, is the probability of a transition due to cause w prior to time t, which can be denoted as:

$$F_w(t \mid X) = \int_0^t S(s \mid X)ds \cdot \Lambda_w(s \mid X), \quad w = 1,2,3,\dots,W \quad (2)$$

$\Lambda_w(s \mid X)$ is the cause-specific cumulative hazard rate for transition w on time t for a certain covariant matrix X. It is defined as $\Lambda_w(t \mid X) = \int_0^t \lambda_w(s \mid x)ds$, with $\lambda_w(t \mid X)$ as defined in Equation 1. $S(s \mid X) = \mathrm{e}^{(-\sum_{w=1}^{W} \Lambda_w(s|x))}$ and represents the overall survival function, which is the probability of remaining unemployed beyond time t. When calculating the cumulative incidence function for transition w, we use the fact that the sum of transition probabilities over w is equal to 1 minus the probability that

[11] For computational convenience, the average level of education for each branch is based on the 2012-13 average, thereby assuming that the in- and out-flow of (un)employed workers over this period does not affect the overall average level of education for workers in a particular branch.

no transition is observed (i.e. a person remains unemployed). To conclude, the Breslow method is used to handle tied failures. The number of effective transitions from unemployment to employment per person is relatively limited in the two years of observation 2012 and 2013. Moreover, we also explored other methods for handling tied failures like Efron, and that did not change our results. Therefore, we have chosen the Breslow method, as it computational less intensive given the large sample, as will be discussed next.

5. Data

5.1. Information on unemployment

This study uses micro-level registration data from Statistics Netherlands and data on job openings from the Employee Insurance Agency in 2012 and 2013. We rely on data of 2012 and 2013, because: (1) the Netherlands experiences the consequences from the Great Recession only as from 2011; and (2) as a result of the economic recession, the Dutch labour market further deteriorated in 2013, relative to 2012. As such, in addition to overall labour market patterns, we look at yearly results to see how such dynamics are potentially influenced by the intensity or duration of a recession, while being able to control for other factors (e.g. seasonal). An alternative interpretation is that we treat 2012 as base-line reference year in the survival model, which we then compare with 2013, while controlling for time-invariant (unobserved) factors.

The data from Statistics Netherlands can be used to monitor the labour market situations of all registered persons in the Netherlands on a daily basis. Regarding unemployment, these data include information on whether persons are actually receiving unemployment insurance benefits. Anyone actively searching for paid labour is considered to be unemployed, however, not everyone receives benefits from the unemployment insurance as this depends on an individual's labour market history. Eligibility to receive unemployment insurance benefits comes with a requirement of consistently having performed paid labour in the period before job loss (i.e. 26 out of the last 36 weeks). Furthermore, the duration of receiving such benefits is contingent on the number of labour years, and capped at a maximum of 38 weeks.

When analyzing the dynamics of (excess) labour supply, we focus only on people who receive unemployment insurance benefits, thereby excluding persons receiving social assistance. While it does occur that people from a status of social assistance transition into a job, this is only true for a relatively

small and declining proportion. Furthermore, the number of assistance recipients is relatively stable, even in times of an economic recession, and fluctuations in labour market patterns are reflected primarily by changes in unemployment insurance (UI) benefit figures.

In Table 1, we present the number of unemployment insurance (UI) benefit recipients and the number of unfilled job openings for2012 and 2013. Between both years there clearly has been a large increase in unemployment insurance benefits (+29%), accompanied by only a relatively minor decrease in outstanding job openings (-6%). As such, the number of vacancies has remained relatively stable, albeit displaying an obvious seasonal pattern. This result indicates that further deterioration of the labour market in 2013 seems to be mainly due to the further increase of unemployment, and not due to a decrease of available job openings.

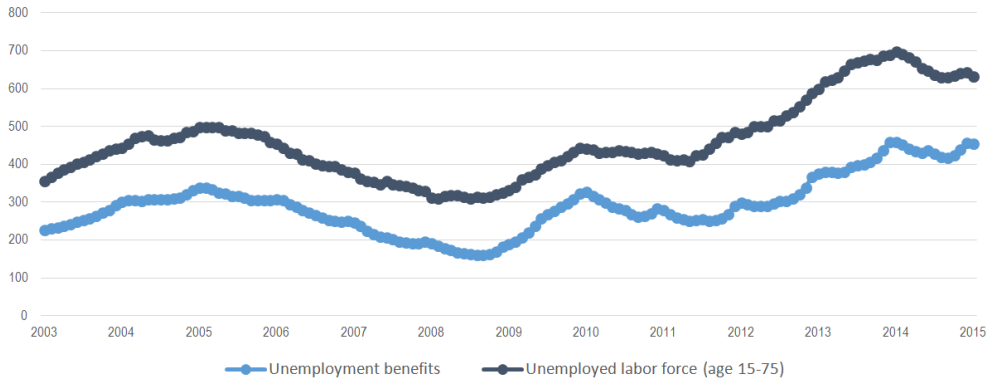
Table 1: Labour Market Excess Supply and Demand

Situation	2012	2013	%
UI benefit recipients	348,500	448,000	+29%
Unfilled job openings	164,000	154,500	-6%

Note: Unemployment insurance (UI) benefit recipients are estimates based on a random 5% sample of the total registered Dutch population for 2012 and 2013.

The administrative data on unemployment only consist of persons who are currently receiving unemployment insurance benefits. As a result, it could be that trends in unemployment are measured inaccurately. Therefore, we compare our data with macro-level data from Statistics Netherlands on unemployment trends on Figure 8. We observe that the trends in number of unemployment insurance benefits and unemployed labour force are similar (i.e. the correlation between both is 0.96). From this we conclude that the micro-level data on number of people with unemployment insurance benefits is a reliable proxy for macro-level trends in unemployment.

Figure 8: Trends in the number of unemployment insurance (UI) benefit recipients and unemployed labour force



Source: Statistics Netherlands

One unique feature of the registration data is that it includes a standard sector classification, the so-called "Standaard Bedrijfsindeling 2008" (SBI 2008), which gives a detailed representation of job types within 21 pre-determined sectors.[12] This study disaggregates the labour market using these 21 sectors (see Table 5 for a description). Furthermore, the registration data provides us with employer identifiers, which are used to calculate employer-specific average education levels. For each person, educational attainment is classified in accordance with the International Standard Classification of Education (ISCED). The first category (ISCED level 1) reflects primary education as the highest attained education level. The second category (ISCED level 2) refers to lower secondary, pre-vocational and the first level of vocational education. The third category (ISCED level 3 or 4) reflect pre-university, upper secondary or the upper three levels of vocational education. The fourth category (ISCED level 5 or 6) indicates that the highest attained education level is a bachelors degree at a university (of applied sciences). The fifth category (ISCED level 7 or 8) indicates that persons have a masters degree or a higher education level.[13] To examine the extent to which crowding out is present in transitions from unemployment to employment, we compare an individual's level of educational attainment with employer- and category-specific averages. In particular, we relate the average level of educational attainment at the former employer (category) to that of the current employer (category). Results are disaggregated by the five

[12] The Dutch Standaard Bedrijfsindeling (SBI 2008) is based on the activity classification of the European Union (Nomenclature statistique des activités économiques dans la Communauté Européenne, NACE) and on the classification of the United Nations (International Standard Industrial Classification of All Economic Activities, ISIC). Source: Statistics Netherlands.

[13] A detailed description of the ISCED codes used can be found at: http://www.uis.unesco.org/Education/Documents/isced-2011-en.pdf

aforementioned levels of educational attainment to see if these transitions differ by level of education.[14]

Table 2 presents the stark heterogeneity in trends for unemployment insurance benefits and unfilled job openings by level of education. For all distinguished education levels we observe a substantial increase between 2012 and 2013 in the number of recipients who receive unemployment insurance (UI) benefits. For most education levels, we also observe a decrease in the number of job openings, but this decrease is relatively smaller than the observed increase in unemployment. Persons with primary education as their highest attained education level are an exception: the increase in unemployment is about as large as the decrease in unfilled job openings.

Table 2: Dutch labour market situation by education category

Education	Situation	2012	2013	%
ISCED 1	UI benefit recipients	*21,500*	*24,000*	*+11*
	Unfilled job openings	*17,500*	*15000*	*-12*
ISCED 2	UI benefit recipients	*54,500*	*72,000*	*+32*
	Unfilled job openings	*48,000*	*46,000*	*-5*
ISCED 3-4	UI benefit recipients	*130,500*	*177,000*	*+35*
	Unfilled job openings	*58,000*	*54,000*	*-7*
ISCED 5-6	UI benefit recipients	*42,500*	*53,500*	*+26*
	Unfilled job openings	*29,000*	*28,000*	*-3*
ISCED 7-8	UI benefit recipients	*17,000*	*21,000*	*+21*
	Unfilled job openings	*12,000*	*11,500*	*-2*
Unknown	UI benefit recipients	*82,000*	*101,000*	*+23*
	Unfilled job openings	-	-	-

5.2. Information on job openings

Information on job openings is received from the Dutch Employee Insurance Agency.[15] This agency obtains information on job openings from "Jobfeed", an advanced internet tool that scans the internet on a daily basis for job openings (https://www.jobfeed.nl). The advantage of this scanning tool is that it

[14] The employer-specific education levels can be calculated in two ways. First, we could transform education levels into years of education and the employer-specific education level would then present the average education years of employees. Alternatively, we use the highest attained education levels to calculate the average employer-specific education level. Because the Netherlands has educational tracking, which among others causes that the route to a certain highest attained education level can vary in terms of education years, we use the education categories to construct the employer-specific education levels instead.

[15] For more information, see: http://www.uwv.nl/OverUWV/english/

can retrieve all announced job openings on the internet and that labour market sectors and required education levels are assigned to each job opening. Moreover, these scanning devices make it possible to register when job openings appear, when persons can no longer apply and it can identify if job openings are announced on multiple websites to prevent double counting. There are also disadvantages when using such online scanning devices, namely: (1) job openings are frequently not announced on the internet and as a result these jobs are not registered; and (2) there are often announcements in which multiple jobs are offered, and it has been proven to be difficult for the scanning devices to identify how many jobs are actually offered.

To overcome these disadvantages, weights have been assigned to the job opening numbers generated by the scanning device underlying "Jobfeed". The assigned weights ensure that the total predicted job openings of Jobfeed are identical to the numbers presented by Statistics Netherlands. Therefore, Statistics Netherlands conducts a large-scale questionnaire among 88.000 employers each year. In this study we have these weighted job opening numbers at our disposal. However, it is unclear whether the numbers of the Statistics Netherlands are more accurate than those generated by Jobfeed. A Dutch report of Statistics Netherlands (Heerschap et al., 2011) indicates that: (1) the predicted number of job openings by Jobfeed is structurally lower than the predicted number of job openings by the Statistics Netherlands; and, perhaps, most importantly (2) the observed trends (fluctuations) of unfilled job openings using Jobfeed or Statistics Netherlands yield figures that are very similar.

6. Results

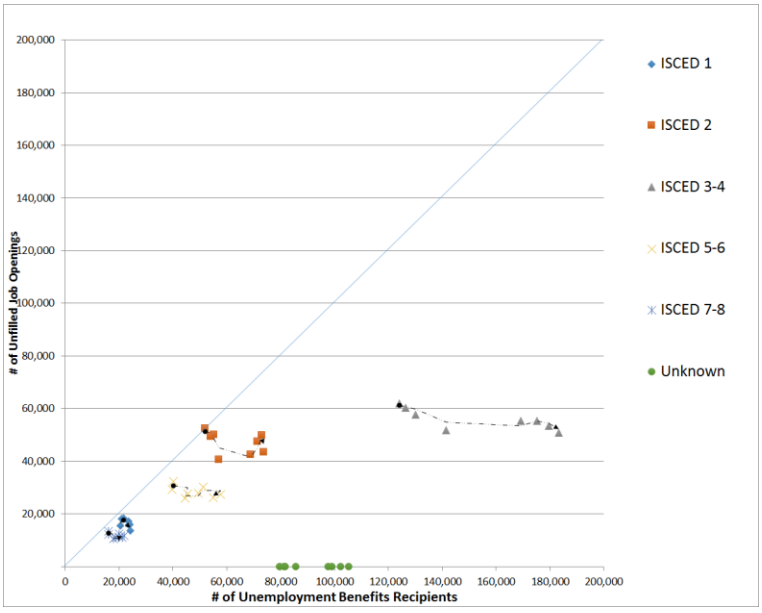
6.1. Beveridge curve using micro-level data

On Figure 9, we present the micro-level results by plotting the number of unemployment insurance benefits recipients against the number of unfilled job openings per yearly quarter and by education attainment. For clarification, this figure is based on the micro-level data (Section 5). The main observations from Figure 9 (and Table 2) are that the labour market has deteriorated for all education levels, but particularly so for individuals with ISCED level 3-4 and to a lesser extent for (older) persons for which the education level is unknown. Notably, these two groups also make up for the largest proportion of the Dutch labour force. For the relatively higher levels of educational attainment (ISCED 5-8), results for unemployment have also deteriorated, but to a lesser extent, and accompanied by a smaller decrease in unfilled job openings.

6.2. Job turnover: key facts

Derived from the underlying numbers of survival graphs (available at the authors upon request), and based on the micro-level data, we indicate that roughly 32% of all UI benefits that started in 2012 had been ended and replaced by a new job before the end of the year, whereas this is only 27% for UI benefits that started in 2013. Moreover it appears that switching is relatively slightly more prevalent in 2013 (15.5% same vs. 14.0% different) than in 2012 (11.8% same vs. 12.3%. different). This difference, albeit minor, is in line with the hypothesis that labour market switching is increasing with the duration or intensity of an economic recession. Furthermore, the largest proportion of jobs is found in a branch of similar level of average education. This can probably be largely attributed to people actually finding a new job in the same branch. The proportion of persons who find jobs with a higher/lower average education level compared to their previous job is similar for 2012 (both 8%) and 2013 (both 7%). These proportions do not provide direct evidence for the notion that people accept jobs in a relatively lower-educated branch during a prolonged time of economic downturn (i.e. the crowding-out hypothesis, see Sub-section 6.3). Education-specific trends in job turnover

Figure 9: Unfilled job openings and unemployment insurance (UI) benefit recipients by education level, 2012-2013



Note: Estimations for unemployment insurance benefits recipients are based on a random 5% sample of the total registered Dutch population for 2012 and 2013. Each dot represents the corresponding number of observations per yearly quarter, as indicated by the dashed-lined arrow. For education level Unknown, no balance between unfilled job openings and unemployment insurance benefits can be depicted due to a lack of the former.

6.3. Education-specific trends in job turnober

6.3.1. Transfers from unemployment to other sectors

Education-specific trends in job turnover are presented in Table 3. This table presents hazard ratios for each of the transitions from unemployment to same or different sector, relative to the reference category (ISCED 3-4). The first column ("No") gives, for each ISCED-level, the percentage of unfinished unemployment spells by the end of the calendar year, as to get insight in the percentage of persons that remain unemployed. Furthermore, the relative hazard ratios are estimated conditional on the background characteristics gender, age, occupational sector, seasonal unemployment insurance (UI) benefit patterns and (temporary) employment provisions across levels of education (see Appendix for full estimation output).

Table 3: Transfers out of unemployment insurance (UI) benefit to new job in same or in different sector, (Relative) hazard ratios by exit/education level

	2012					**2013**				
	Hazard (Ratios)					**Hazard (Ratios)**				
	No	same	diff.	unk.	other	no	same	diff.	unk.	other
ISCED 1	1.03	0.99	0.66*	0.74	2.09*	1.09*	0.89	0.49*	1.13	1.60*
ISCED 2	1.01	0.88*	0.86*	0.82	1.35*	1.01	0.84*	0.81*	0.94	1.32*
ISCED 3-4	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
ISCED 5-6	0.89*	1.22*	1.24*	1.68*	0.95	0.92*	1.25*	1.42*	1.61*	1.06
ISCED 7-8	0.88*	1.15	1.38*	1.92*	1.19	0.88*	1.35*	1.36*	2.89*	1.25
Unknown	1.10	0.99	0.88*	0.82	1.31*	1.08	0.99	0.92	1.60*	1.31*

Note: * denotes statistical significant difference, relative to the reference category, at the 5% level. Estimations are based on a random 5% sample of the total registered Dutch population for 2012 and 2013. Full estimation results are available in the Appendix. ISCED Level 3-4 is reference education level, for which estimated transition hazards are presented for each exit option. Relative hazard ratios for each education level are estimated conditional on gender, age, occupational sector, seasonal unemployment insurance (UI) benefit patterns and (temporary) employment provisions through employment agencies and recruitment companies.

Our findings show that persons with ISCED levels 1 or 2 have the lowest probability of finding a job, and if they do find a job, then it usually concerns a job in the same sector as before the period of unemployment. This could indicate that lower educated persons are relatively restricted to one labour market sector, which might lower their odds of finding a new job after being unemployed. The opposite is found for the persons with ISCED 5-8 education levels. Not only is the probability of finding a new job after unemployment substantially higher compared to persons with lower education levels, they also

switch relatively often to jobs in different labour market sectors. For persons with unknown education levels, the estimation results are most similar to ISCED levels 3-4, with the notable exceptions of their higher rates for (1) no transition from unemployment to employment within the calendar year, and (2) transitioning into a non-job situation. Knowing that this group 'unknown' consists of relatively old labour force participants, this can, at least, partially be attributed to the fact that they have had a long labour market history. As such, they will have longer unemployment insurance (UI) benefit rights. Also, some of them will have had the option to retire (early) upon termination of their unemployment insurance (UI) benefit situation. It might also indicate that they find it more difficult to find a job, indicating that labour market prospects are relatively poor for older labour force participants.

Lastly, the percentage of persons who remain unemployed has increased substantially for all education levels, which underlines that the crisis on the Dutch labour market continued (and perhaps even intensified) in 2013. The differences in relative hazard ratios between the education categories appears to be more pronounced in 2013, which might indicate that educational differences in terms of employment opportunities are magnified in times of prolonged recession. With respect to labour market sector switching, on average, the results indicate that people in the labour force tend to switch more frequently in 2013, which could imply they are more willing to accept jobs in other labour market sectors as the recession continues. Switching between labour market sectors becomes relatively unlikely for persons with ISCED levels 1-2, when comparing 2013 to 2012, which again indicates that the lowest educated persons are more confined to one labour market sector and rely more strongly on job opportunities within their sector.

6.3.2. Crowding-out

To investigate if crowding out could be a potential mechanism affecting transitions from unemployment to employment, the same duration model is estimated again, but this time labeling transfers from unemployment to a new job by comparing the average level of education in the previous branch (i.e. before unemployment) to the average level of education of the new branch (i.e. after period of receiving unemployment insurance (UI) benefit). Table 4 shows the estimation results in similar fashion as Table 3 (see Appendix Table A2 for full regression results).

The estimation results show that persons with the highest levels of educational attainment (ISCED 5-8) not only have the highest overall rates of finding a job, but also that they more often switch to a more

highly educated branch (relative to the branch of their previous job). The opposite is found for persons with low levels of educational attainment (ISCED 1-2) who have the lowest overall rates job finding rates and less often switch to a more highly educated branch. Interestingly, and consistent with the empirical results in Table 4, it appears to be the case that if persons with ISCED 1-2 find a job, there is relatively more often no change in average level of education for the branch.

When comparing the estimation results between 2012 and 2013, we find that the differences in relative hazard ratios between the education categories are generally more pronounced in 2013. This indicates, first of all, and again, that educational differences in terms of employment opportunities tend to get magnified in times of recession. Second, we find for higher educated persons that the continuation of the recession did also negatively affect their probability of finding a job. But apparently, when jobs are available to them, it is generally in relatively highly educated branches of industry.

Table 4: Transfers out of unemployment insurance (UI) benefit to new job requiring same, lower, or higher level of education, (Relative) hazard ratios by exit/education level

	2012						**2013**					
	Hazard (Ratios)						**Hazard (Ratios)**					
	no	higher	same	lower	unk.	other	no	higher	same	lower	unk.	other
ISCED 1	1.03	0.69*	1.08	0.52*	0.74	2.09*	1.09*	0.55*	0.88	0.56*	1.13	1.60*
SCED 2	1.01	0.83*	0.90	0.89	0.82	1.35*	1.01	0.81*	0.87*	0.79*	0.94	1.32*
ISCED 3-4	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
ISCED 5-6	0.89*	1.54*	1.11	1.17*	1.68*	0.95	0.92*	1.91*	1.18*	1.08	1.61*	1.06
ISCED 7-8	0.88*	1.56*	1.12	1.25*	1.92*	1.19	0.88*	1.88*	1.35*	1.00	2.89*	1.25
Unknown	1.10*	0.83*	1.00	0.96	0.82	1.31*	1.08*	0.97	0.95	0.95	1.60*	1.31*

Note: Asterisk * denotes statistical significant difference, relative to the reference category, at the 5% level. Estimations are based on a random 5% sample of the total registered Dutch population for 2012 and 2013. Full estimation results are available in the Appendix. ISCED Level 3-4 is reference education level, for which estimated transition hazards are presented for each exit option. Relative hazard ratios for each education level are estimated conditional on gender, age, occupational sector, seasonal unemployment insurance (UI) benefit patterns and (temporary) employment provisions through employment agencies and recruitment companies.

Taken together, the observed estimation patterns do not provide evidence for the theory of crowding-out effects. In 2012, the results seem partially supportive for crowding-out effects, in the sense that the average education level of the branch after unemployment is often lower than the branch before unemployment compared to persons who are lower educated. However, for 2013 no empirical support is found and also when comparing 2013 to 2012, there appears to be no evidence that higher-educated persons more frequently transition into jobs for which they might be relatively over-qualified. In that

sense, higher-educated persons do not push lower-educated persons into jobs for which they are over-qualified. Instead of a crowding-out effect, the empirical results seem to indicate that lower education persons (ISCED 1-2) are isolated in their labour market sectors, which could negatively influence their labour market opportunities.

6.4. Sector-specific trends in job turnover

There are 21 sectors on the Dutch labour market and they are listed in Table 5. Column three shows the number of jobs in a certain labour market sector as a percentage share of the total number of jobs. The table shows that the labour market sector G (wholesale and retail trade; repair of motor vehicles and motorcycles) and Q (Human health and social work activities) are the largest labour market sectors, while there are virtually no jobs in labour market sectors A (Agriculture, forestry and fishing), B (Mining and quarrying), D (Electricity, gas, steam and air conditioning supply), E (Water supply; sewerage, waste management and remediation) and U (Extraterritorial organisations and bodies). For the latter labour market sectors, it implies that there are insufficient or no observations available to estimate reliable hazard rates. Figure 10 gives a visual overview of the hazard rates aggregated at the sector level. For clarification, these hazard rates were derived from individual-level estimates, controlling for gender, age, seasonality of unemployment insurance benefits, educational attainment, the provision of (temporary) employment placement and pay-rolling through employment agencies and recruiting companies.

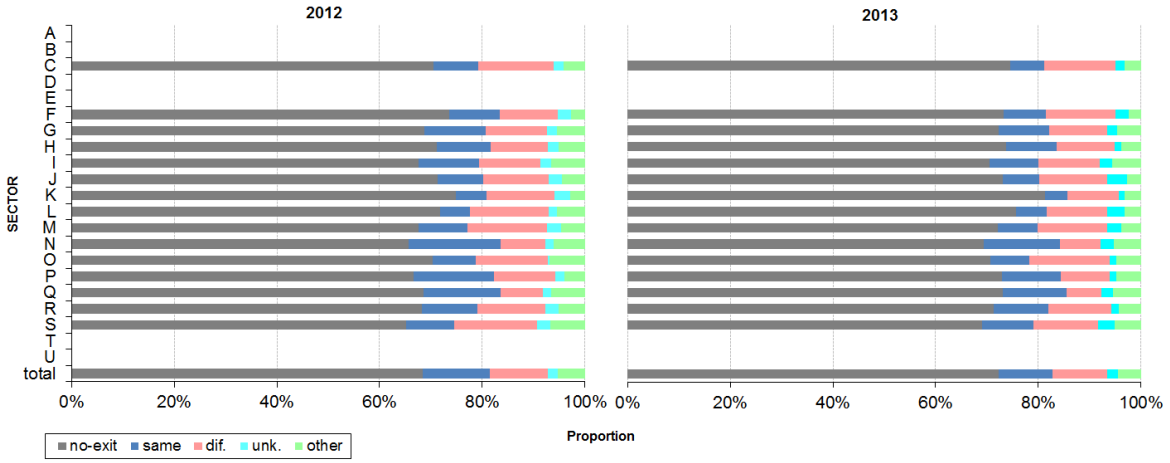
Figure 10 indicates that job turnover to other labour market sectors is virtually observed across all sectors. There is quite some heterogeneity in the ratios between finding a job in the same/different sector, and the degree of heterogeneity depends on the size of the sector. For larger labour market sectors (see Table 5), lower fractions of sector switches is observed. Lastly, for some sectors (e.g. F: Construction) a notable increase in the relative switching between sectors in 2013 can be partially understood in the context of relatively large layoffs that year for these specific sectors.

Table 5: Share of total number of paid jobs by labour market sectors, 2012-2013

Letter	Sector Description	share (%)
A	Agriculture, forestry and fishing	*1.1*
B	Mining and quarrying	*0.1*
C	Manufacturing	*8.3*
D	Electricity, gas, steam and air conditioning supply	*0.3*
E	Water supply; sewerage, waste management and remediation	*0.4*
F	Construction	*3.8*
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	*14.6*
H	Transportation and storage	*4.2*
I	Accommodation and food service activities	*3.9*
J	Information and communication	*2.6*
K	Financial institutions	*2.9*
L	Renting, buying and selling of real estate	*0.8*
M	Consultancy, research and other specialised business services	*5.5*
N	Renting and leasing of tangible goods and other business support services	*8.5*
O	Public administration, public services and compulsory social security	*5.7*
P	Education	*5.9*
Q	Human health and social work activities	*15.4*
R	Culture, sports and recreation	*1.5*
S	Other service activities	*1.6*
T	Activities of households as employers	*0.5*
U	Extraterritorial organisations and bodies	*0.0*
-	Missing	*12.5*

Note: Labour market shares are based on a random 5% sample of the total registered Dutch population and averages are presented for the years 2012 and 2013. For more details on the different labour market sectors, see: http://www.cbs.nl/NR/rdonlyres/1A454D8E-CF57-4828-9A14-319A464DAEC3/0/sbi2008versie2014engels.pdf.

Figure 10: Transfers out of unemployment insurance (UI) benefit to new job in same or different Sectors, (Relative) hazard ratios by exit/sector



7. Conclusion

The findings in this study suggest that transitions from unemployment to a job in the same sector (as before unemployment) occur about as frequently as transitions from unemployment to a job in a different sector (as before unemployment). Moreover, this inter-sectoral mobility is increasing with a person's level of educational attainment and it is relatively more prevalent in 2013 than in 2012. This difference between years supports the hypothesis that prolonged periods of labour market deterioration promote labour market mobility. There are, however, important differences between levels of educational attainment, with lower levels of educational attainment (ISCED 1-2) being relatively confined to their initial sector. The empirical results do not support the presence of crowding-out effects, in the sense that we do not observe that higher-educated persons move into jobs previously occupied by relatively low-educated workers in periods of labour market downturn, thereby pushing out the latter. Instead of a crowding-out effect, the empirical results seem to indicate that lower education persons (ISCED 1-2) are isolated in their labour market sectors, which could negatively influence their labour market opportunities.

Current Dutch labour market policies tend to focus on people with relatively poor labour market opportunities (e.g. older workers, ethnic minorities, persons with a lower education level), and in general label subgroups within the labour force as to generate more effective policies in a more efficient manner. One of these subgroups is the labour market sector in which 'at-risk' persons are employed,

and an underlying assumption, which is often not expressed, is that labour market prospects of persons are sector-specific. Our results clearly show that labour markets are not sector-specific and this casts doubts on whether labour markets can be improved effectively and efficiently by dogmatic sector-specific policies. Generally, it is unclear how to identify feasible labour markets for individuals or specific subgroups in the labour force. Therefore, a fruitful research avenue would be to determine such feasible labour markets as to facilitate effective labour market policies.

To conclude, we refer again to the Beveridge curve for the Netherlands, and argue that it did not shift, partly owing to the employability of skills of the high-educated across sectors, and partly because of the relatively high allocative efficiency of the Dutch labour market (compared to other countries in the Euro Area). Job turnover can thus mitigate some of the consequences of a recession under the condition that: (1) the labour market is able to allocate workers to jobs efficiently; (2) the allocation of workers to jobs yields better fits in terms of education; and (3) it exhibits a countercyclical pattern.

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Appendix A: Full estimation tables

TABLE A0: Key statistics on vacancies and unemployment in the Netherlands (x1,000) in 2012 and 2013

	2005				2006				2007			
	Q1	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
[1.] Labour demand												
Unfilled vacancies (V)	148.8	141.3	163.7	165.3	187.3	209.7	230.1	230.3	234.9	238.3	246.8	249.3
Filled vacancies (F)	9119	9245	9275	9196	9279	9412	9488	9526	9569	9739	9818	9790
Total number of jobs (K)	9267.8	9386.3	9438.7	9361.3	9466.3	9621.7	9718.1	9756.3	9803.9	9977.3	10064.8	10039.3
Job openings, % (V/K)	**1.6%**	**1.5%**	**1.7%**	**1.8%**	**2.0%**	**2.2%**	**2.4%**	**2.4%**	**2.4%**	**2.4%**	**2.5%**	**2.5%**
[2.] Labour supply												
Employment (E)	7739	7812	7857	7866	7845	7905	7977	8027	8052	8156	8227	8241
Unemployment (U)	528	497	463	466	483	425	383	386	408	352	328	330
Persons in labour force (L)	8267	8309	8320	8332	8328	8330	8360	8412	8460	8509	8556	8571
Unemployment, % (U/L)	**6.4%**	**6.0%**	**5.6%**	**5.6%**	**5.8%**	**5.1%**	**4.6%**	**4.6%**	**4.8%**	**4.1%**	**3.8%**	**3.9%**

	2008				2009				2010			
	Q1	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
[1.] Labour demand												
Unfilled vacancies (V)	247	244.9	246.7	197.4	153.9	128.4	130.7	125.4	115.6	117.5	125.3	128.3
Filled vacancies (F)	9820	9937	9973	9923	9857	9881	9852	9819	9706	9855	9859	9841
Total number of jobs (K)	10067	10181.9	10219.7	10120.4	10010.9	10009.4	9982.7	9944.4	9821.6	9972.5	9984.3	9969.3
Job openings, % (V/K)	**2.5%**	**2.4%**	**2.4%**	**2.0%**	**1.5%**	**1.3%**	**1.3%**	**1.3%**	**1.2%**	**1.2%**	**1.3%**	**1.3%**
[2.] Labour supply												
Employment (E)	8269	8359	8399	8406	8399	8390	8360	8296	8228	8279	8305	8299
Unemployment (U)	351	320	292	309	364	368	378	414	471	434	415	421
Persons in labour force (L)	8620	8679	8691	8715	8763	8758	8737	8710	8699	8713	8720	8720
Unemployment, % (U/L)	**4.1%**	**3.7%**	**3.4%**	**3.5%**	**4.2%**	**4.2%**	**4.3%**	**4.8%**	**5.4%**	**5.0%**	**4.8%**	**4.8%**

	2011				2012				2013			
	Q1	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
[1.] Labour demand												
Unfilled vacancies (V)	135.1	134.7	134.7	122.7	117.4	109.3	106.6	101.7	96.3	91.3	95.1	96.5
Filled vacancies (F)	9866	9983	9994	9963	9878	9989	9926	9897	9726	9829	9823	9775
Total number of jobs (K)	10001.1	10117.7	10128.7	10085.7	9995.4	10098.3	10032.6	9998.7	9822.3	9920.3	9918.1	9871.5
Job openings, % (V/K)	**1.4%**	**1.3%**	**1.3%**	**1.2%**	**1.2%**	**1.1%**	**1.1%**	**1.0%**	**1.0%**	**0.9%**	**1.0%**	**1.0%**
[2.] Labour supply												
Employment (E)	8232	8259	8301	8327	8283	8327	8368	8341	8259	8273	8280	8253
Unemployment (U)	451	412	414	460	513	500	504	547	631	633	651	672
Persons in labour force (L)	8683	8671	8715	8787	8796	8827	8872	8889	8890	8906	8932	8925
Unemployment, % (U/L)	**5.2%**	**4.8%**	**4.7%**	**5.2%**	**5.8%**	**5.7%**	**5.7%**	**6.2%**	**7.1%**	**7.1%**	**7.3%**	**7.5%**

	2014				2015				2016			
	Q1	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
[1.] Labour demand												
Unfilled vacancies (V)	104.1	107.5	113.4	118.8	124.9	130.3	132.9	142.7	150.5	155.1		
Filled vacancies (F)	9650	9811	9788	9840	9732	9914	9934	9949	9844	10018		
Total number of jobs (K)	9754.1	9918.5	9901.4	9958.8	9856.9	10044.3	10066.9	10091.7	9994.5	10173.1		
Job openings, % (V/K)	**1.1%**	**1.1%**	**1.1%**	**1.2%**	**1.3%**	**1.3%**	**1.3%**	**1.4%**	**1.5%**	**1.5%**		
[2.] Labour supply												
Employment (E)	8146	8190	8250	8270	8235	8296	8332	8311	8287	8386		
Unemployment (U)	721	668	620	629	664	615	586	591	605	557		
Persons in labour force (L)	8867	8858	8870	8899	8899	8911	8918	8902	8892	8943		
Unemployment, % (U/L)	**8.1%**	**7.5%**	**7.0%**	**7.1%**	**7.5%**	**6.9%**	**6.6%**	**6.6%**	**6.8%**	**6.2%**		

Source: Statistics Netherlands.

Note 1: K=F+V

Note 2: L=E+U

TABLE A1.a: Transfers out of unemployment insurance (UI) benefit to new job in same or in different sector (Full Estimation Results (Hazard ratios) for 2012)

	(1) Same		(2) Different		(3) Unknown	
	coef.	(s.e.)	coef.	(s.e.)	coef.	(s.e.)
Male	1.18***	(.05)	1.37***	(.16)	0.81***	(.05)
April-June	0.78***	(.04)	0.94	(.12)	1.03	(.08)
July-Sep	0.55***	(.03)	0.60***	(.08)	0.67***	(.05)
Oct-Dec	0.10***	(.01)	0.07***	(.02)	0.04***	(.01)
15-26 years	2.11***	(.13)	1.80***	(.28)	3.21***	(.3)
27-34 years	1.38***	(.08)	1.30*	(.19)	1.53***	(.15)
45-54 years	0.83***	(.06)	0.86	(.14)	0.60***	(.07)
55+ years	0.35***	(.04)	0.53***	(.12)	0.80	(.11)
ISCED 1	0.66***	(.08)	0.74***	(.22)	2.09***	(.25)
ISCED 2	0.86**	(.05)	0.82	(.13)	1.35***	(.11)
ISCED 5-6	1.24***	(.08)	1.68***	(.25)	0.95	(.11)
ISCED 7-8	1.38***	(.12)	1.92***	(.39)	1.19	(.18)
ISCED unknown	0.88*	(.06)	0.82	(.13)	1.31***	(.13)
Temporary work	1.32**	(.18)	1.00	(.29)	0.90	(.12)
Sector A	2.89***	(.46)	1.41	(.84)	0.97	(.4)
Sector B	.	.	.	.	.	.
Sector C	1.36***	(.12)	0.96	(.24)	0.95	(.15)
Sector D	1.66	(.63)	1.70	(1.72)	0.79	(.79)
Sector E	1.20	(.49)	1.29	(1.3)	1.14	(.81)
Sector F	1.16	(.11)	1.59**	(.35)	0.70*	(.13)
Sector H	1.03	(.12)	1.13	(.32)	1.22	(.21)
Sector I	1.03	(.12)	1.13	(.32)	1.22	(.19)
Sector J	1.05	(.13)	1.10	(.33)	1.11	(.24)
Sector K	1.09	(.13)	1.37	(.38)	0.54**	(.15)
Sector L	1.61**	(.32)	0.75	(.54)	1.56	(.54)
Sector M	1.28***	(.11)	1.18	(.27)	0.98	(.16)
Sector N	0.56***	(.08)	0.91	(.27)	1.55***	(.23)
Sector O	1.06	(.19)	0.00	.	1.49	(.39)
Sector P	0.87	(.1)	0.69	(.21)	0.85	(.17)
Sector Q	0.60***	(.06)	0.73	(.17)	1.24*	(.15)
Sector R	1.00	(.15)	1.17	(.4)	1.04	(.25)
Sector S	1.30**	(.16)	1.10	(.38)	1.22	(.26)
Sector T	1.46	(.47)	1.01	(1.03)	0.34	(.34)
Sector U	.	.	.	.	.	.
Number of observations	17313		17313		17313	
Number of failures	2344		373		1036	
pseudo- R 2	0.040		0.044		0.060	

Note: */**/*** denote significance at 10/5/1% level (two-sided). Regression estimates for relative hazard ratios are based on a random 5% of the total Dutch population. The reference category is: UI-spell started in Jan-Mar, age category 35-44 years old., education level category is ISCED 3-4, non-temporary work, and labour market sector G.

TABLE A1b: Transfers out of unemployment insurance (UI) benefit to new job in same or in different sector (Full Estimation Results (Hazard ratios) for 2013)

	(1) Same		(2) Different		(3) Unkown	
	coef.	(s.e.)	coef.	(s.e.)	coef.	(s.e.)
Male	1.29***	(.05)	1.69***	(.17)	0.85**	(.06)
April-June	0.82***	(.04)	0.78**	(.08)	0.85**	(.06)
July-Sep	0.85***	(.04)	0.53***	(.07)	0.41***	(.04)
Oct-Dec	0.23***	(.03)	0.06***	(.04)	0.08***	(.04)
15-26 years	2.43***	(.13)	2.81***	(.36)	3.58***	(.34)
27-34 years	1.40***	(.08)	1.51***	(.2)	1.90***	(.19)
45-54 years	0.85**	(.05)	0.72**	(.11)	0.77**	(.09)
55+ years	0.30***	(.03)	0.53***	(.11)	0.75*	(.11)
ISCED 1	0.49***	(.07)	1.13	(.28)	1.60***	(.23)
ISCED 2	0.81**	(.05)	0.94	(.13)	1.32***	(.11)
ISCED 5-6	1.42***	(.08)	1.61***	(.23)	1.06	(.11)
ISCED 7-8	1.36***	(.11)	2.89***	(.48)	1.25	(.18)
ISCED unknown	0.92	(.05)	1.60***	(.2)	1.31***	(.12)
Temporary work	1.04	(.13)	1.25	(.27)	1.01	(.14)
Sector A	2.44***	(.41)	1.97	(.91)	1.21	(.47)
Sector B	.	.	.	.	.	.
Sector C	1.41***	(.11)	0.85	(.18)	0.78	(.12)
Sector D	0.98	(.44)	0.00	.	0.49	(.49)
Sector E	1.63	(.4)	1.69	(1.)	0.49	(.35)
Sector F	1.56***	(.11)	1.39*	(.26)	0.67**	(.11)
Sector H	1.19*	(.12)	0.59	(.19)	0.96	(.18)
Sector I	1.07	(.1)	1.23	(.29)	1.21	(.18)
Sector J	1.24**	(.13)	1.94***	(.43)	0.69	(.17)
Sector K	0.94	(.12)	0.54	(.22)	0.79	(.19)
Sector L	1.12	(.21)	1.82	(.68)	0.70	(.27)
Sector M	1.12	(.1)	1.16	(.24)	0.86	(.14)
Sector N	0.68***	(.08)	1.25	(.29)	1.32*	(.19)
Sector O	1.36**	(.2)	0.46	(.27)	1.03	(.3)
Sector P	0.70***	(.08)	0.50**	(.16)	1.32*	(.22)
Sector Q	0.53***	(.05)	1.25	(.22)	1.14	(.13)
Sector R	1.14	(.16)	0.73	(.31)	1.03	(.26)
Sector S	1.02	(.14)	1.58	(.44)	1.01	(.22)
Sector T	1.04	(.43)	1.36	(1.37)	0.51	(.51)
Sector U	.	.	.	.	.	.
Number of observations	21725		21725		21725	
Number of failures	2749		525		1072	
pseudo- R 2	0.026		0.034		0.033	

Note: */**/*** denote significance at 10/5/1% level (two-sided). Regression estimates for relative hazard ratios are based on a random 5% of the total Dutch population. The reference category is: UI-spell started in Jan-Mar, age category 35-44 years old., education level category is ISCED 3-4, non-temporary work, and labour market sector G.

TABLE A2a: Transfers out of unemployment insurance (UI) benefit to new job requiring higher, same, or lower level of education (Full regression results (Hazard ratios) for 2013)

	(1) Higher		(2) Same		(3) Lower		(4) Unknown	
	coef.	(s.e.)	coef.	(s.e.)	coef.	(s.e.)	coef.	(s.e.)
Male	1.08	(.06)	1.18***	(.05)	1.29***	(.08)	1.37***	(.16)
April-June	0.82***	(.06)	0.57***	(.03)	0.77***	(.05)	0.94	(.12)
July-Sep	0.58***	(.04)	0.52***	(.03)	0.55***	(.04)	0.60***	(.08)
Oct-Dec	0.11***	(.01)	0.08***	(.01)	0.11***	(.01)	0.07***	(.02)
15-26 years	1.74***	(.14)	1.68***	(.1)	2.26***	(.18)	1.80***	(.28)
27-34 years	1.17**	(.09)	1.33***	(.08)	1.45***	(.11)	1.30*	(.19)
45-54 years	0.82**	(.07)	0.97	(.06)	0.75***	(.07)	0.86	(.14)
55+ years	0.35***	(.05)	0.60***	(.06)	0.35***	(.05)	0.53***	(.12)
ISCED 1	0.69**	(.1)	1.08	(.1)	0.52***	(.1)	0.74	(.22)
ISCED 2	0.83**	(.07)	0.90*	(.05)	0.89	(.07)	0.82	(.13)
ISCED 5-6	1.54***	(.13)	1.11	(.07)	1.17*	(.1)	1.68***	(.25)
ISCED 7-8	1.56***	(.19)	1.12	(.11)	1.25**	(.14)	1.92***	(.39)
ISCED unknown	0.83**	(.07)	1.00	(.06)	0.96	(.08)	0.82	(.13)
Temporary work	0.83	(.12)	3.02***	(.39)	0.72**	(.12)	1.00	(.29)
Sector A	1.58*	(.4)	2.10***	(.43)	0.54	(.27)	1.41	(.84)
Sector B	.	.	.	.	.	.	.	.
Sector C	1.46***	(.15)	0.56	(.07)	1.29**	(.17)	0.96	(.24)
Sector D	0.67	(.48)	0.58	(.41)	2.50**	(1.13)	1.70	(1.72)
Sector E	1.13	(.57)	0.24	(.24)	1.66	(.84)	1.29	(1.3)
Sector F	1.15	(.13)	0.90	(.1)	1.22	(.16)	1.59**	(.35)
Sector H	0.99	(.14)	1.00	(.13)	0.91	(.16)	1.13	(.32)
Sector I	1.20	(.15)	1.07	(.13)	0.68**	(.13)	1.13	(.32)
Sector J	0.62**	(.11)	0.66**	(.12)	1.60***	(.25)	1.10	(.33)
Sector K	0.33***	(.08)	0.32***	(.07)	2.17***	(.3)	1.37	(.38)
Sector L	0.79	(.26)	0.53*	(.2)	2.23***	(.55)	0.75	(.54)
Sector M	0.44***	(.07)	0.69***	(.08)	2.37***	(.26)	1.18	(.27)
Sector N	0.80	(.12)	0.75**	(.1)	0.98	(.16)	0.91	(.27)
Sector O	0.25***	(.1)	0.76	(.18)	1.69**	(.36)	0.00	.
Sector P	0.33***	(.06)	1.68***	(.18)	1.32*	(.19)	0.69	(.21)
Sector Q	0.55***	(.06)	1.08	(.1)	1.29**	(.15)	0.73	(.17)
Sector R	0.65**	(.13)	0.88	(.16)	1.27	(.25)	1.17	(.4)
Sector S	0.60**	(.12)	0.84	(.15)	1.83***	(.3)	1.10	(.38)
Sector T	0.61	(.36)	0.65	(.33)	3.80***	(1.14)	1.01	(1.03)
Sector U	.	.	.	.	.	.	.	.
Number of observations	17313		17313		17313		17313	
Number of failures	1358		2379		1364		373	
pseudo- R 2	0.040		0.048		0.044		0.044	

Note: */**/*** denote significance at 10/5/1% level (two-sided). Regression estimates for relative hazard ratios are based on a random 5% of the total Dutch population. The reference category is: UI-spell started in Jan-Mar, age category 35-44 years old., education level category is ISCED 3-4, non-temporary work, and labour market sector G.

TABLE A2b: Transfers out of unemployment insurance (UI) benefit to new job requiring higher, same, or lower level of education (Full regression results (Hazard ratios) for 2013)

	(1) Higher		(2) Same		(3) Lower		(4) Unknown	
	coef.	(s.e.)	coef.	(s.e.)	coef.	(s.e.)	coef.	(s.e.)
Male	1.17***	(.06)	1.29***	(.06)	1.45***	(.08)	1.69***	(.17)
April-June	0.87**	(.05)	0.83***	(.04)	0.76***	(.05)	0.78**	(.08)
July-Sep	0.86**	(.06)	0.77***	(.04)	0.73***	(.05)	0.53***	(.07)
Oct-Dec	0.23***	(.04)	0.19***	(.03)	0.20***	(.04)	0.06***	(.04)
15-26 years	2.39***	(.17)	1.71***	(.11)	2.26***	(.17)	2.81***	(.36)
27-34 years	1.27***	(.1)	1.15**	(.07)	1.39***	(.1)	1.51***	(.2)
45-54 years	0.94	(.08)	0.89*	(.06)	0.74***	(.06)	0.72**	(.11)
55+ years	0.28***	(.04)	0.67***	(.06)	0.31***	(.04)	0.53**	(.11)
ISCED 1	0.55***	(.1)	0.88	(.1)	0.56***	(.11)	1.13	(.28)
ISCED 2	0.81***	(.06)	0.87**	(.05)	0.79***	(.06)	0.94	(.13)
ISCED 5-6	1.91***	(.14)	1.18**	(.08)	1.08	(.09)	1.61***	(.23)
ISCED 7-8	1.88***	(.21)	1.35***	(.13)	1.00	(.11)	2.89***	(.48)
ISCED unknown	0.97	(.07)	0.95	(.06)	0.95	(.07)	1.60***	(.2)
Temporary work	0.65***	(.08)	2.37***	(.27)	0.64***	(.1)	1.25	(.27)
Sector A	1.51	(.39)	1.98***	(.42)	0.51	(.26)	1.97	(.91)
Sector B	.	.	.	.	.	.	.	.
Sector C	1.27**	(.12)	0.57***	(.07)	1.43***	(.15)	0.85	(.18)
Sector D	0.57	(.4)	0.28	(.28)	1.63	(.82)	0.00	.
Sector E	0.73	(.33)	0.00	(.)	2.72***	(.75)	1.69	(1.)
Sector F	1.54***	(.14)	0.89	(.09)	1.38***	(.15)	1.39*	(.26)
Sector H	1.35**	(.16)	1.13	(.13)	0.77	(.13)	0.59	(.19)
Sector I	1.41***	(.15)	0.95	(.12)	0.59***	(.11)	1.23	(.29)
Sector J	0.68**	(.11)	0.50***	(.09)	2.05***	(.27)	1.94***	(.43)
Sector K	0.27***	(.07)	0.31***	(.08)	1.82***	(.27)	0.54	(.22)
Sector L	0.80	(.21)	0.58*	(.17)	1.18	(.32)	1.82	(.68)
Sector M	0.34***	(.05)	0.59***	(.07)	2.32***	(.24)	1.16	(.24)
Sector N	1.04	(.13)	0.97	(.12)	1.04	(.15)	1.25	(.29)
Sector O	0.49**	(.13)	0.63*	(.16)	2.39***	(.41)	0.46	(.27)
Sector P	0.21***	(.04)	1.27**	(.14)	1.49***	(.2)	0.50**	(.16)
Sector Q	0.58***	(.06)	1.09	(.09)	1.02	(.11)	1.25	(.22)
Sector R	0.77	(.15)	1.31*	(.21)	1.35	(.26)	0.73	(.31)
Sector S	0.51***	(.11)	1.06	(.17)	1.53**	(.25)	1.58	(.44)
Sector T	0.71	(.41)	1.24	(.56)	1.99	(.9)	1.36	(1.37)
Sector U	.	.	.	.	.	.	.	.
Number of observations	21725		21725		21725		21725	
Number of failures	1635		2249		1547		525	
pseudo- R 2	0.030		0.024		0.028		0.034	

Note: */**/*** denote significance at 10/5/1% level (two-sided). Regression estimates for relative hazard ratios are based on a random 5% of the total Dutch population. The reference category is: UI-spell started in Jan-Mar, age category 35-44 years old, education level category is ISCED 3-4, non-temporary work, and labour market sector G.

Do Nurses React to Inter-Industry Wage Differentials? – Evidence of Nursing Graduates in the Netherlands

Sofie Cabus

Abstract

This paper explores the extent to which inter-industry wage differentials can explain the decision of nursing graduates to quit the life sciences and health industry (LSH). Using the theoretical framework of Lazaer (2009), it is predicted that nurses drop-out of LSH in case their weighted general skills pay-off more in foreign industries than seniority in LSH. It is also predicted that industries demanding rigorous specific skills are prone to skill shortages. The empirical strategy benefits from data of the Dutch higher vocational school leaving monitor on abilities necessary to perform in the job. Owing to iterative one-to-one matching, we make 2003 to 2011 graduates homogenous with respect to their general skills. The results are in line with the predictions: nurses, who leave LSH, can earn significantly higher wages of about 2 percent. This estimate is particularly driven by female nurses and vertical industry mobility.

Keywords: Ability; Nurses; Recruitment bottlenecks; Skills; Wage Differentials

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1. Introduction

Recruitment bottlenecks in the life sciences and health industry (LSH) are worrisome, and will become problematic, as in most developed countries, population ageing increasingly put stress on the demand for health care services (Hurd, 1973; Jones and Gates, 2004; Heitmueller and Inglis, 2007; Cedefop, 2010; Maestad et al., 2010; World Health Organization, 2011). The European Center for the Development of Vocational Training (Cedefop) indicates that `skill shortages', defined as individuals without credentials or skills considered `valid' to enter the job, are underlying recruitment bottlenecks. There are two broad explanations why skill shortages arise. First, there are not enough individuals who study in the field of nursing, so that the demand for nurses is greater than the supply of nurses. The LSH industry may well suffer from bad image problems, relative to other industries, so that the industry is not able to attract individuals in health and welfare education or training. Second, those who studied in the field of nursing, leave the LSH industry early and, thus, switch to another industry. This paper particularly focusses on the latter reason of skill shortages in LSH by exploring the labor market prospects of graduates in the field of nursing or midwifery.[16]

The previous literature present several potential reasons of leaving the LSH industry: nurses are underpaid (Taylor, 2007; Di Tommaso et al., 2009); compared to other industries, health professionals and associates have to work hard and irregular hours, and face, in some cases, life threatening risks on the job (Shields and Ward, 2001; Shields, 2004; Yildirim and Aycan, 2008; Di Tommaso et al., 2009); professions as nursing are considered female professions and, thus, less attractive to men (Maestad et al., 2010); the costs (or student investment) of attending nursing education and training and the lack of student loans (Yett, 1966); and some researchers discuss the work-family conflict (Yildirim and Aycan, 2008). This paper contributes to the previous literature by exploring the extent to which inter-industry wage differentials can explain the decision to quit LSH. As wages are a composite measure of the return to (innate) ability, education in school, experiences on-the-job, and background characteristics (e.g. Mincer, 1958; Becker, 1962, 1964), inter-industry wage differentials can tell us something more about the demand and supply of nurses' skills, and the return to these skills, in and out of LSH. From this, the rise (and fall) of recruitment bottlenecks, or else the rise (and fall) of skill shortages as a result of switching from LSH to other industries, can be explored. The previous literature on wage differentials focused on differences in earnings by gender (e.g. Groshen, 1991; Jones and Gates, 2004); by race or

[16] Throughout this paper, graduates in the field of nursing or midwifery are abbreviated by `nursing' or `nurses'.

ethnicity (e.g. Lam and Liu, 2002; Heywood and Halloran, 2004; Heywood and Parent, 2012); by health status (e.g. Johnson and Lambrinos, 1985; and Kidd et al., 2000); or by type of education program (e.g. Booton and Lane, 1985; Gill and Leigh, 2003). This paper focuses on inter-industry wage differentials for apparently similar workers. The central question of this paper is then: can an individual, with nursing credentials, who is not employed in the LSH industry but in 'foreign' industries[17], do better than a nurse in LSH employment?

This paper contributes to the previous literature on inter-industry wage differentials of nursing graduates by the integration of the skill-weights approach (Lazaer, 2009) with an empirical analysis in one country (the Netherlands). To our best knowledge, the fairly recent theoretical model has not yet been applied in previous research, in particularly not in research with regard to employment in the LSH industry. We use repeated cross-section data on the school-to-work decision of about 5,000 nurses or midwives working in the Netherlands in different sectors over the period 2003 to 2011. These health professionals filled in the Dutch higher vocational education school-leaving questionnaires (HBO monitor) one year after graduation from their studies. The fact that nurses are observed very early in their career is considered as a particular contribution of this paper to the literature, whereas previous work focused on later stages of the nursing career (e.g. Shields and Ward, 2001).

2. Wage differentials and job-related skills in the literature

Old and recent theoretical and empirical studies are discussing why differences in wages between similar workers in different industries exist. We start with the early work of Krueger and Summer (1986). Their work is mainly on the inter-industry wage structure. They argue that across countries: *"[...] the wage structure is very similar for different types of workers. Certain industries pay all types of workers high wages and others paying all types of workers relatively low wages (p.2)."* Krueger and Summer (1986) conclude that the competitive labor market model, in which firms compete against each other, (and which should impose competitive wages,) should be modified in order to explain the observed inter-industry wage variations. They argue for a non-competitive explanation dealing with efficiency wages and rent-sharing between firms and workers.

[17] Throughout this paper, we will often refer to the concept of 'foreign industries'. Unless otherwise stated, foreign does not refer to industries in other countries than the Netherlands, i.e. abroad, but other-than-LSH industries. This facilitates the notation.

Dickens and Katz (1987) confirm these findings of Krueger and Summer (1986). They have analyzed the differences in wages for both union and nonunion workers across time, countries and industries. The authors argue the persistency of these wage differentials, even after controlling for individual background characteristics and job location. Dickens and Katz (1987) also show that individuals who switch from low to high paying industries receive a considerable share of the industry wage premium. They conclude that job-related ability and work experience may play an important role in explaining the persistency of the observed differences in wages, aside from differences in job quality or compensating wage differentials.

Gibbons and Katz (1992) present in their work two different explanations with respect to wage differentials between industries. On the one hand, they argue that the underlying worker population between distinct industries may substantially differ with respect to unobserved job-related ability, so that differences in worker productivity drive the observed wage differential, and not the type of industry (see also Roy, 1951). On the other hand, Gibbons and Katz (1992) argue that, if it is possible to construct a research design wherein apparently similar workers can be compared, then `true' wage differentials can be observed, in essence, as a result of: (1) compensating wage differentials; (2) rent-sharing; and (3) efficiency wages. Note that these two explanations are also similar to those put forth by Krueger and Summer (1986).[18]

A more recent study of Handy and Katz (1998) provides an example with respect to inter-industry wage structure differences. The authors examine the differences in wages between nonprofit organizations and corporations. Overall, the authors observe lower wages in the nonprofit sector than in the for-profit sector. Handy and Katz (1998) argue that the observed wage differentials are actually advantageous for the nonprofit sector, as it generates consumer trust and self-selection of employees in managerial positions. This selectivity is called positive, as it attracts desirable workers in nonprofits compared to for-profits. Melly (2005) also describes wage differentials between public and private sector employees in Germany. She explores these wage differentials by gender and by educational attainment. The author argues that women have higher differences in wages between the public sector and the private sector than men. Melly (2005) also observes that, compared to the private sector, wages in the public sector are more equally distributed across different educational levels.

[18] Having both explanations empirically tested, Gibbons and Katz (1992) conclude that there is no theoretical model in the literature that is able to motivate their estimated wage differentials between industries.

Recent previous research also distinguishes between general and job-specific skills. The focus of this evidence is rather on wage growth and earnings profiles than on estimating inter-industry wage differentials. For example, Dustmann and Pereira (2008) analyze the returns to tenure and experience in two countries, namely: the United Kingdom and Germany. Taking two countries, the authors aim at exploring how wages are affected by two totally different labor market regulations and training systems. They find that a flexible labor market system, such as in the UK, yield higher returns to experience, than the German system with relatively strict employment protection. Dustmann and Pereira (2008) argue that, owing to the German apprenticeship system, graduates from vocational education have higher wages in the short run. However, in the long run, wage growth of these graduates is limited, flattening life-time returns to experiences. These short run and long run labor market outcomes are also observed by Hanushek et al. (2011) for 18 countries, and Cabus and Haelermans (2013) for the Netherlands.

Relatively new in explaining inter-industry wage differentials, is the skill-weights approach of Lazaer (2009). The author modeled a skill-weights approach particularly for understanding wage differences between stayers (those who stay in the industry) and leavers (those who switch industry).[19] The starting point is that credentials signal two types of skills: (1) general skills; and (2) industry-specific skills. For instance, the former type of skills can be used in the LSH and the foreign industry, whereas the latter only contribute to the productivity at the LSH industry. Lazaer (2009, p.914) argues in this respect: *"Firm-specific human capital raises the productivity of the worker at the current firm, but not elsewhere, setting up a bilateral monopoly situation between the worker and firm."* The skills-weights approach puts forth that not all industries attach the same weight to the skills an individual acquired in his/her (school) career. For instance, the LSH industry attaches high weights to health and welfare skills, such as taking blood from a patient. These skills are considered irrelevant in foreign industries (e.g. a nurse who would become a saleswoman in a department store). In conclusion, the skill-weights model predicts that nurses switch to foreign industries in case their general skills pay-off more in foreign industries than seniority in LSH. It also predicts that industries in need of rigorous specific (vocational) skills are prone to recruitment bottlenecks.

[19] Note that we adapt his general theory directly to the choice of working in the LSH industry. Thus, Lazaer (2009) did not use nursery as an example in his work.

3. The Life Sciences and Health Industry in the Netherlands

3.1. Facts and figures

This paper explores the employment decision of graduates in the field of nursing in the Netherlands. The LSH industry in the Netherlands is an interesting case study for at least three reasons. First, the life sciences and health industry is a top industry: it captures about 14.9 percent of the Dutch Gross Domestic Product (i.e. an investment per capita of about €5,392); the industry is considered an important employer giving work to 178,435 nurses and 43,630 life sciences and health professionals (Statistics Netherlands, 2012); and the total revenue of the life sciences and health industry is estimated at 17.7 billion euros in 2010 (Dutch life sciences outlook, 2012; Statistics Netherlands, 2011).

Second, there is a lively policy debate in the Netherlands on health professionals' labor market prospects in the LSH industry. The Amsterdam Economic Board argues in their `Human Capital Agendas' that managing talent will play a critical role in innovation and growth of the LSH industry (see Amsterdam Economic Board, 2012). In this respect, the LSH industry formulates three goals: (1) to develop new or change old education or training programs in accordance with the development of the LSH industry; (2) to foster close cooperation between modern LSH activities, the companies in the industry (regional or national), and LSH education or training programs; and (3) to improve job attractiveness of the LSH industry.

Third, government officials recently discussed policy measures in order to cut health care costs in 2014 (rijksoverheid.nl, 2013). If government officials and policy makers would make the LSH industry less attractive, relative to other industries, then this calls for an in-depth research on the consequences for (the attractiveness of) employment in the LSH industry.

3.2. Wage setting of nurses

In the Netherlands, nurses earn an average gross monthly wage of 2,725 euros when working 40 hours per week and 4.33 weeks per month. Comparing the Dutch gross monthly wages to those of the neighboring countries, 3,833 euros in the United Kingdom, 3,241 euros in Belgium, and 2,858 euros in Germany, it is concluded that nurses' purchasing power parities in the Netherlands are ranked latest (Kevätsalo, 2007; loonwijzer.nl, 2014). Note that, in the Netherlands, the majority of nurses working in the LSH industry are having a part-time contract. This is not surprisingly, given that the union density is

relatively low in the Netherlands (i.e. the lowest compared to UK, Belgium, and Germany), and given that LSH employers are often third sector organizations.

4. Conceptual framework

In the first instance, the theoretical model used in this paper aims at offering an interpretation of wage differentials between LSH and other, 'foreign' industries, by using the skill-weights approach of Lazaer (2009). Note that 'foreign' in this context does not refer to industries in other countries than the Netherlands, i.e. abroad, but other-than-LSH industries. It facilitates the notation as follows. In the second instance, the theoretical model offers an interpretation for skills shortages in LSH, as a result of switching to other, 'foreign' industries by using the concept of *market thickness*.

4.1. Inter-industry wage differentials

The starting point is that every nurse has two types of skills A and B. Let A denote the general skills, and B the industry-specific skills, so that every nurse has a skill set (A, B). The weights attached to the skill set of the nurse in the LSH industry is denoted by λ_1, whereas the weights attached to skills in the 'foreign' (F) industry is denoted by λ_2. Note that $\lambda \sim \mathrm{U}[0,1]$ follows a uniform distribution. Following Lazaer (2009), we present the output of a nurse in the LSH industry as $\lambda_1 \mathrm{A} + (1-\lambda_1)\mathrm{B}$, and the output of a nurse in the F industry as $\lambda_2 \mathrm{A} + (1-\lambda_2)\mathrm{B}$. Nurses are paid according to their output in each industry.

There are two periods $\mathrm{t} \in \{1,2\}$. In the first period $(\mathrm{t}=1)$, the individual graduates from health and welfare education or training. In the second period $(\mathrm{t}=2)$, a nurse can make a decision between staying in the LSH industry or leaving to the F industry. The level of the wage (W) a nurse will earn in the second period is equal to the return to the skill set (A, B). If a nurse decides to stay in LSH, the outside offer λ_2 will be rewarded as `seniority'. In order to stay in LSH, the outside offer λ_2 should be worse than the LSH job offer λ_1. Otherwise, the nurse could do better elsewhere, so that she decides to leave LSH voluntary. As such, the main assumption underlying the skill-weights approach is that nurses only quit in case they would do better elsewhere. The wage of an individual who stays and who leaves can then be formally expressed as (Lazaer, 2009, p.920):

$$\mathrm{W}_{stay} = \mathrm{B} + \frac{1}{2}(\lambda_1 + \mathrm{E}(\lambda_2|\lambda_2 < \lambda_1)(\mathrm{A}-\mathrm{B}) , \qquad (1)$$

$$\mathrm{W}_{quit} = \mathrm{B} + \frac{1}{2}(\lambda_1 + \mathrm{E}(\lambda_2|\lambda_2 > \lambda_1)(\mathrm{A}-\mathrm{B}). \qquad (2)$$

Consequently, the inter-industry wage differential between nurses who quit and who stay can then be formally expressed as (Lazaer, 2009, p.924):

$$W_{quit} - W_{stay} = \frac{1}{2}[E(\lambda_2|\lambda_2 > \lambda_1) - E(\lambda_2|\lambda_2 < \lambda_1)](A - B) ,$$

$$W_{quit} - W_{stay} > 0 , \qquad (3)$$

where the expression $(A - B)$ denotes the difference between general skills and industry-specific skills, and the estimated wage differential is unambiguously positive. Note that specific skills B are cancelled out from equation (3) when subtracting W_{stay} from W_{quit}.

4.2. Market thickness

Market thickness particularly deals with (A-B). Consider the following two extreme cases: (1) very thick markets; and (2) very thin markets. In the extreme case that there would only be one industry, the LSH industry, and no other industries, having nursing credentials would become obvious for an individual to connect with the labor market, so that these skills are considered general. Consequently, if the LSH industry is thick, then nurses get more offers from which they can choose. In this extreme case, $(A - B)$ is equal to zero and one would not estimate a wage differential ($W_{quit} - W_{stay}$=0). However, in the extreme case that the market is very thin, industry-specific skills are not transferable to other, foreign industries. If there would be only one industry, the LSH industry, wherein nursing credentials are suitable, among many other foreign industries, health and welfare education or training becomes a risky investment because: *"[...] wage loss associated with job turnover is greater in very thin markets than in very thick markets (Lazaer (2009, p.925).*" Thus, the average wage offer (λ) on the foreign labor market for an individual who heavily invested in B, and not in A, will be worse compared to individuals who heavily invested in A, and not in B. Thus, the thinner the market, the higher the risk of investment in B in terms of bad labor market outcomes. Thin markets are, therefore, prone to recruitment bottlenecks.

5. Empirical strategy

5.1. The intuition

Estimating inter-industry wage differentials induce problems of self-selection of individuals into LSH employment (Rubin, 1974). For instance, women are more likely than men to become nurse or midwife (Jones and Gates, 2004). Individuals may have an entirely different motivation to work in LSH, simply based on gender, race or ethnicity, or cultural differences. However, we argue that these determinants of motivation also play a key role in enrolling in health and welfare education or training necessary to perform in an LSH job. The probability that an individual will start in an LSH profession depends on studying in the field of health and welfare, and these individual probabilities to enroll in health and welfare education or training reflect the (initial) motivation of students to go into LSH (see also Botelho et al., 1998). Thus, comparing only individuals with credentials in nursing, already enhances comparability between these health professionals in different industries (this is also confirmed in Section 6).

Nonetheless, selectivity bias can still occur at the start of employment: individuals can diverge from their initial thought of going into LSH and, consequently, apply for work in foreign sectors. This decision to 'switch' may be associated with, for instance, individual background characteristics (e.g. gender, ethnicity, innate ability, and motivation), on the one hand, or regional variation in employment opportunities (i.e. the number of vacancies, the availability of hospitals, and structure of the LSH industry) (e.g. Booton and Lane, 1985; Elliot et al., 2007), on the other hand. We deal with the former type of selectivity by using iterative one-to-one matching models. Here, the idea is that individuals with nursing credentials who do not work in the LSH industry are matched, based on their general job-related skills, with individuals having the same credentials, but who do work in the LSH industry (see also Gibbons and Katz, 1992). Indeed, the mathematical theory (Section 4) shows that, when computing inter-industry wage differentials, nurses' industry-specific skills are cancelled out, and, consequently, do not give rise to the estimated inter-industry wage differentials. As such, we do not have to match nurses based on job-specific skills. In addition, we only look at nurses who graduated at most one year ago from their studies. Job market experience in LSH is, thus, limited.

General skills will be expressed as an index (see Section 6). They are a composite measure of innate ability, individual characteristics, education in school, and, to some extent, experience on-the-job. Thus, because of matching on job-related abilities, we can control for observed and unobserved differences

between nurses' general skills underlying potential wage differences (see critiques of Gibbons and Katz, 1992).

We deal with the latter type of selectivity by using regional fixed effects models. These fixed effects models are particularly useful within the scope of regional variation in employment opportunities, which are considered difficult to change in the short run (e.g. the availability of hospitals).

5.2. Formal expression

Consider an individual $\mathrm{i} \in \{1,2,\ldots \mathrm{N}\}$ who studied in the field of nursing. Having studied in this field is a necessary condition in order to work as nurse, midwife or related health (associate) profession. At time $(\mathrm{t} = 1)$, the graduated individual has to make a decision to stay in LSH, or to switch industry. Assume that the decision of the individual is based on the attractiveness of LSH at time t, relative to other sectors. We express the level of attractiveness by the hourly wages (y_i) one can earn when working in a particular industry.

Let I denote a treatment indicator that takes the value of 0 if individuals choose to stay in LSH; and 1 if otherwise. We then may write the average treatment effect of the treated as (see Cameron and Trivedi (2005):

$$\mathrm{E}(\mathrm{y}_{1i}|\mathrm{I} = 1) - \mathrm{E}(\mathrm{y}_{0i}|\mathrm{I} = 0)\,,$$

$$\text{if studied health profession} = 1\,, \qquad (4)$$

where y_{1i} denotes the wages observed for a treated student, and y_{0i} the wages observed for a control student.

We can rewrite equation (4) as:

$$\mathrm{E}(\mathrm{y}_{1i} - \mathrm{y}_{0i}|\mathrm{I} = 1) + \{\mathrm{E}(\mathrm{y}_{0i}|\mathrm{I} = 1) - \mathrm{E}(\mathrm{y}_{0i}|\mathrm{I} = 0)\}\,,$$

$$\text{if studied health profession} = 1. \qquad (5)$$

The first term denotes the average treatment effect of the treated, and the second term the bias that may be estimated owing to self-selection of graduates into LSH employment. Self-selection gives rise to omitted variables bias, in case selection on observable and unobservable variables takes place. In order

to deal with selection into LSH employment, we consider the functional form of the labor market outcome `wages' (Mincer, 1958; Becker, 1962, 1964):

$$y_i \sim f(\alpha_i; \nu_i; \xi_i; X_{ji}). \qquad (6)$$

Equation (6) argues that the level of the wages one can earn in the labor market depends on: (innate) ability α_i; education ν_i; experience ξ_i; and a vector X_{ji} of individual, family and neighborhood characteristics. From this functional form of y_i we can argue that untreated students are comparable to treated students, when they have, on average, the same level of innate ability, education and experience. And also based on their background characteristics, they are, on average, the same. As such, if treated and untreated students are comparable as previously argued, wage differentials can only be explained by the hourly wages y_i one can earn when working in different occupations (i.e. LSH, or not).[20] Wage differentials can, thus, be defined as the difference in wages of comparable, homogenous individuals (with respect to $\alpha_i; \nu_i; \xi_i; X_{ji}$) working in different industries.

An important step in our empirical strategy is to make treated and untreated graduates, on average, comparable with respect to: $\alpha_i; \nu_i; \xi_i; X_{ji}$ (see also the critiques of Gibbons and Katz, 1992). Therefore, we propose to match individuals, who studied in the field of nursing, and who are not in LSH, to individuals, who also studied in this field, but who do work in LSH. We use iterative one-to-one matching of treated individuals (i.e. those who switch) to untreated individuals (i.e. those who stay) based on their observed set of general skills. We perform 500 one-to-one matching iterations in total, each time using a random sorting of the data. See Section 6 for more information on the validity and reliability of the set of abilities used in this paper. These abilities are partly endowed (α_i), and have been formed by the family and the neighborhood wherein individuals grow up (X_{ji}), but also by education in schools (ν_i), and also by experience on the job (e.g. internships) (ξ_i). Thus, we argue that, under the assumption that the set of abilities measured is sufficiently informative with respect to the individuals (cap)abilities to perform well in the job, we are able to capture observed and unobserved differences between control group and treatment group with respect to: $\alpha_i; \nu_i; \xi_i; X_{ji}$. Owing to one-to-one matching based on job-related abilities, the distribution of job-related abilities is, on average, the same for treated and matched untreated students. Note that we can test for this latter assumption to hold (see Section 0).

[20] Note that, if treated and untreated students are, on average, comparable, their reservation wage should also be, on average, comparable. In this case, the problem of censored observations is ignorable (see Cabus and Haelermans, 2013).

We also condition on the variation in attractiveness of industries between municipalities (m_k, with $\mathrm{k} \in \{1,2,\ldots,\mathrm{K}\}$). Employment rates can differ between cities in the Netherlands, among other reasons, because of the availability of hospitals, clinics, pharmacy, and other LSH business-related activities. Regional variation can bias the results, as students who have keen interest in studying in the field of nursing, and, consequently, in being employed in a good hospital or care center, are likely to, for example, perform their internship in this good hospital in order to increase their chances on the LSH job market. The attractiveness of LSH employment can substantially differ between municipalities, among other reasons, because of the availability of hospitals, clinics, pharmacy and other LSH related businesses. We deal with regional variation in employment opportunities by using regional fixed effects models. Fixed effects models grasp features of the municipality that are considered fixed (municipality-specific) and, as such, features that are not easily to alter in the short run (e.g. the availability of hospitals or health education programs).

There are two caveats. First, regional fixed effects models also controls for regional variation in the wage rate, and, consequently, the (attractiveness of the) LSH industry within that region compared to other sectors. Note, however, owing to the public nature of the LSH sector, large differences in wages between municipalities are not expected. Second, institutions and courses can have an influence on the development of general and specific skills. As such, instead of regional fixed effects models, one could also estimate course or educational institution fixed effects models in order to further control for unobserved individual and course characteristics (e.g. peer effects). We do not estimate these fixed effects models, however, because of data limitations. If one would estimate an institution or course fixed effects model, the total number of observations within each cluster, given our data set, would be too limited in order to estimate any significant results.

5.3. Multivariate regressions

After having performed iterative one-to-one matching, the multivariate regression estimates the difference in wages between comparable, homogenous workers in the different industries. We now construct a weighted standardized index of requested job-related general skills r_i by using principal components analysis (in Section 6, we show that, owing to rich data on job-related ability, index r_i is valid and reliable). We then may write:

$$\mathrm{y}_i = \mathrm{cte} + \beta \mathrm{I}_i + \gamma \mathrm{r}_i + \theta(\mathrm{I}_i \times \mathrm{r}_i) + \varepsilon_{m_k i} ,$$

if studied health profession $= 1$. (7)

y_i denotes the log of hourly wages; I_i the treatment indicator; r_i requested job-related general skills; ($I_i \times r_i$) the interaction between the treatment indicator and requested job-related general skills; and $\varepsilon_{m_k i}$ the error term. Note that regional fixed effects models are clustering the standard error at the level of m_k. The estimate of θ denotes the wage differential. θ captures the variance in wages that cannot be explained by differences in own or requested job-related general skills. We control for requested job-related general skills, so that positive differences in wages are not attributable to asking more skills (or productivity), but, instead, are the result of weighting the same skills differently.

6. Data

We use repeated cross section data of the Dutch higher vocational school leaving monitor (HBO) over the period 2003 to 2011. The data consist of (1) individual characteristics and job-related (cap)abilities of individuals; (2) educational features as type of education, educational program, field of education, and level of education; and (3) job characteristics as hourly wages, job hours, job search, field of the job, level of the job, skill use and skills short to perform in the job, and self-reported job match.

One year after graduation, all respondents were sent the school-leaving questionnaire (roa.unimaas.nl/hbomonitor). Every year about 600 graduates (10 percent) in nursing participated, so that we have (N=5,157) individuals in our sample in total. We observe that 14.66 percent of graduates (N=756) in the field of nursing dropped out of LSH only one year after graduation. From these 'dropouts', 114 (15.08 percent) are male, and 642 (84.92 percent) are female. In total, 617 male nurses are observed in the data, and 4,540 female nurses. As such, relatively, more males (18.48 percent) than females (14.14 percent) are leaving LSH one year after graduation.

Table 6: Industries in which the switchers are employed

		Freq.	Perc.			Freq.	Perc.
1	armed forces	2	0.27	26	administrative associate professionals	16	2.14
2	legislators, senior officials and managers	2	0.27	27	social work associate professionals	48	6.43
3	legislators and senior government officials	1	0.13	28	secretaries and keyboard-operating clerks	1	0.13
4	corporate managers	10	1.34	29	numerical clerks	3	0.4
5	production and operations managers	13	1.74	30	material-recording and transport clerks	5	0.67
6	managers of small enterprises	2	0.27	31	library, mail and related clerks	1	0.13
7	professionals	59	7.9	32	other office clerks	2	0.27
8	computing professionals	4	0.54	33	cashiers, tellers and related clerks	2	0.27
9	architects, engineers and related professionals	26	3.48	34	client information clerks	5	0.67
10	teaching professionals	2	0.27	35	travel attendants and related workers	1	0.13
11	secondary education teaching profession	19	2.54	36	housekeeping and restaurant services workers	2	0.27
12	primary and pre-primary education teacher	15	2.01	37	personal care and related workers	106	14.19
13	special education teaching professional	3	0.4	38	other personal services workers	1	0.13
14	other teaching professionals	2	0.27	39	protective services workers	4	0.54
15	business professionals	17	2.28	40	shop, stall and market salespersons	5	0.67
16	legal professionals	1	0.13	41	fishery workers, hunters and trappers	1	0.13
17	social science and related professional	279	37.35	42	machinery mechanics and fitters	1	0.13
18	writers and creative or performing artists	2	0.27	43	electrical and electronic equipment mechanics	1	0.13
19	public service administrative professionals	1	0.13	44	assemblers	1	0.13
20	technicians and associate professionals	14	1.87	45	motor vehicle drivers	1	0.13
21	physical and engineering science technicians	13	1.74	46	domestic and related helpers, cleaners	3	0.4
22	computer associate professionals	3	0.4	47	manufacturing laborers	1	0.13
23	optical and electronic equipment operators	37	4.95				
24	safety and quality inspectors	1	0.13				
25	finance and sales associate professionals	8	1.07				
					Total	747	100

Table 6 presents the industries in which the switchers are employed. The industries are categorized by using the international standard classification of occupations (ISCO). We observe that 37.35 percent of individuals with nursing credentials are employed in social science and related professions; 14.19 percent in personal care; and 6.43 percent in social work. These professions are to some extent related to professions in LSH, so that we classify these individuals' switch as horizontal mobility. However, we also track nurses in many different kinds of occupations, such as architects, engineers and related professionals (3.48 percent); corporate managers (1.34 percent); physical and engineering science technicians (1.74 percent); and shop, stall and market salespersons (0.67 percent). Here, we classify these individuals' switch as vertical mobility. In order to control for `horizontal and vertical industry mobility' in the multivariate regressions in Section 0, we create a dummy variable. The value of one indicates being employed in social sciences, social work or personal care; and the value of 0 otherwise.

7. Descriptive statistics

Table 7 summarizes the descriptive statistics of the variables: (1) hourly wages and log of hourly wages; (2) individual characteristics (i.e. age, gender, ethnicity and province of employment); (3) study program information (i.e. internship, and type of education); and (4) the questions with respect to own ability and requested ability for the job. We report the total number of observations, the mean values and differences between the mean values of the control group and the treatment group. The final column presents the T-values of an independent sample T-test.

The wages of nurses in the Netherlands is equal to about 15.32 euros per hour. This corresponds to the wages observed in the official Dutch statistics (loonwijzer.nl, 2014). In order to account for potential differences in working conditions between LSH-stayers and LSH-leavers, we choose not to work with gross monthly wages, but, instead, with hourly wage rates. Table 2 also summarizes descriptive statistics with respect to the log of hourly wages. We take the logarithm of wages, as to account for the parametric assumptions underlying multivariate regressions (see Section 0). We observe that, without controlling for covariates or following matching procedures, nurses who switch to other industries than LSH earn significantly +3 percent more than stayers.

Table 7: Descriptive statistics of the treated (N=756) and untreated individuals (N=4401) with respect to individual and program characteristics (before matching).

	Mean Tg	Std Dev Tg	Mean Cg	Std Dev Cg	Diff Tg-Cg	T-value
Outcome						
Hourly wage (euros)	15.32	4.81	14.75	4.64	-0.57	-3.1
Hourly wage (log)	2.685	0.2962	2.6522	0.2722	-0.0327	-3
Individual characteristics						
age	30.22	9.35	27.72	8.04	2.5	7.7
gender (male=1)	0.1508	0.3581	0.1143	0.3182	0.037	2.9
non-Western migrant	0.0582	0.2343	0.045	0.2073	0.013	1.6
Western migrant	0.0265	0.1606	0.0275	0.1635	-0.001	-0.2
not a migrant	0.9153	0.2786	0.9275	0.2593	-0.012	-1.2
Study program information						
full time program	0.5304	0.4994	0.6128	0.4872	-0.082	-4.3
part time program	0.2804	0.4495	0.1347	0.3415	0.146	10.3
dual program	0.1892	0.3919	0.2524	0.4345	-0.063	-3.8
internship(yes=1)	0.9496	0.2189	0.9749	0.1563	-0.025	-3.9
Job province						
Groningen	0.0694	0.2544	0.0595	0.2365	0.01	1.1
Friesland	0.0592	0.2362	0.0541	0.2263	0.005	0.6
Drenthe	0.0347	0.183	0.0234	0.1511	0.011	1.9
Overijssel	0.0551	0.2283	0.0674	0.2507	-0.012	-1.3
Gelderland	0.1212	0.3266	0.1231	0.3286	-0.002	0.2
Utrecht	0.077	0.2668	0.1047	0.3062	-0.028	-2.4
Noord-Holland	0.1251	0.3311	0.1145	0.3184	0.011	0.9
Zuid-Holland	0.2237	0.417	0.2191	0.4137	0.005	0.3
Zeeland	0.0139	0.117	0.0159	0.1249	-0.002	-0.4
Noord-Brabant	0.157	0.364	0.147	0.3541	0.01	0.7
Limburg	0.0509	0.22	0.0606	0.2387	-0.01	-1.1
Flevoland	0.0128	0.1124	0.0108	0.1033	0.002	0.5

Table 8: Descriptive statistics of the control group (Cg) and the treatment group (Tg) with respect to own and requested abilities (before matching).

	Mean Tg	Std Dev Tg	Mean Cg	Std Dev Cg	Diff Tg-Cg	T-value
own abilities (scale 1 to 5): ability to…						
apply field-specific knowledge in practice	3.78	0.67	3.86	0.64	-0.09	-3.39
use ICT	3.69	0.74	3.71	0.77	-0.02	-0.81
communicate in foreign languages	2.85	1.06	2.9	1.02	-0.05	-1.22
gather information	3.98	0.64	3.99	0.62	-0.01	-0.32
recognize problems and opportunities	3.99	0.63	3.99	0.61	0	0.07
draw connections	4.01	0.63	3.99	0.62	0.03	1.04
distinguish main priorities from side issues	3.91	0.63	3.92	0.62	0	-0.18
reason logically	4.04	0.62	4.05	0.61	-0.01	-0.33
work within budget/plan/guideline	3.63	0.81	3.56	0.82	0.07	2.23
work well under pressure	4.04	0.71	4.07	0.69	-0.03	-1.26
take decisive action	3.85	0.72	3.79	0.73	0.06	2.08
come up with new ideas and solutions	3.93	0.69	3.83	0.69	0.1	3.55
learn new things	4.17	0.66	4.19	0.62	-0.01	-0.52
make meaning clear to others	3.98	0.67	4.04	0.67	-0.06	-2.21
cooperate productively with others	4.15	0.64	4.25	0.61	-0.1	-4.06
mobilize the capacities of others	3.78	0.69	3.7	0.73	0.08	2.93
perform your work without supervision	4.32	0.63	4.27	0.64	0.06	2.28
requested abilities (scale 1 to 5)						
apply field-specific knowledge in practice	3.71	0.94	4.01	0.79	-0.3	-9.48
use ICT	3.43	0.96	3.43	0.95	0	0.04
communicate in foreign languages	2.03	1.06	2.26	1.04	-0.23	-5.69
gather information	3.76	0.92	3.85	0.83	-0.08	-2.56
recognize problems and opportunities	4.06	0.83	4.14	0.75	-0.08	-2.84
draw connections	4.01	0.86	4.18	0.73	-0.17	-5.88
distinguish main priorities from side issues	3.94	0.78	4.04	0.71	-0.11	-3.8
reason logically	3.97	0.8	4.08	0.71	-0.11	-4.01
work within budget/plan/guideline	3.56	1.06	3.55	1	0	0.08
work well under pressure	4.1	0.86	4.3	0.75	-0.2	-6.69
take decisive action	3.88	0.89	3.91	0.82	-0.03	-1.07
come up with new ideas and solutions	3.86	0.9	3.84	0.84	0.01	0.38
learn new things	3.84	0.92	3.99	0.84	-0.15	-4.47
make meaning clear to others	4.14	0.8	4.17	0.71	-0.03	-1.15
cooperate productively with others	4.16	0.79	4.27	0.72	-0.12	-4.18
mobilize the capacities of others	3.85	0.84	3.93	0.78	-0.08	-2.75
perform your work without supervision	4.35	0.72	4.36	0.69	-0.01	-0.41

Next, consider the individual characteristics of our sample. Overall, we observe only minor differences between treated and untreated individuals with respect to their characteristics. Only with respect to the type of study program, we observe significant mean differences between treated and untreated individuals. For instance, in the control group, there are significant fewer individuals who studied in part-time programs, and significant more individuals who studied in full-time and dual programs. And, on average, untreated individuals are about three years older than treated individuals.

Table 8 summarizes the descriptive statistics of own and requested job-related abilities. With respect to own job-related abilities, 7 out of 17 items have significant T-values (5 percent level), namely: (1) the ability to apply field-specific knowledge in practice (t=-3.39); (2) the ability to take decisive action (t=-2.08); (3) the ability to come up with new ideas and solutions (t=3.55); (4) the ability to make meaning clear to others (t=-2.21); (5) the ability to cooperate productively with others (t=-4.06); (6) the ability to mobilize the capacities of others (t=2.93); (7 the ability to perform your work without supervision (t=2.28). Note that the differences between the treatment group and the control group are always rather small.

Not surprisingly, we find 11 out of 17 items with respect to requested job-related abilities to be significantly different between the control group and the treatment group (see Table 8). Requested abilities to perform well in the job significantly differ between employment in LSH and foreign sectors. The highest mean difference between the control group and the treatment group is observed with respect to the question: ability to apply field-specific knowledge in practice (t=-9.48).

Based on the variables of Table 8, we construct two measures of ability, namely: (1) own job-related general skills; and (2) requested job-related general skills. Therefore, we use principal component analysis in order to reduce the dimension of having 17 items measuring ability into only 1 variable. Note that we have standardized the items, and only retain the first component constructed by the factor analysis. The own job-related general skills measure has an eigenvalue of 6.2169 (ρ=0.3657); the average inter-item correlation is 0.3077; and the scale reliability coefficient Cronbach's alpha is equal to 0.8831. The requested job-related general skills measure has an eigenvalue of 7.5401 (ρ=0.4436); the average inter-item correlation is 0.3893; and the scale reliability coefficient Cronbach's alpha is equal to 0.9155. From these statistics, we conclude that the own job-related general skills measure as well as the requested job-related general skills measure are valid and reliable.

8. Results

8.1. Matching results

In the first instance, we estimate the likelihood of a nurse to be in LSH employment conditional on his/her own job-related abilities by a discrite choice model (probit). Note that the responses on the ability questions were standardized before estimating the probit model. The results of the probit model are available upon request.

The results indicate that, on the one hand, individuals are likely to stay in LSH, if they are able to: apply field-specific knowledge into practice; work well under pressure; make meaning clear to others; and cooperate productively with others. On the other hand, they are more likely to switch, if they are able to work within budget/plan/guideline; come up with new ideas and solutions; mobilize the capacities of others; and perform your work without supervision.

As follows, we check whether the matching made `stayers' and `leavers' comparable with respect to their job-related abilities. Recall that we have matched treated individuals to untreated individuals based on own job-related ability.

Figure 11 and Figure 12 plot the distribution of both ability measures by employment in LSH (dotted line) or F (solid line), after iterative one-to-one matching. The Kolmogorov Smirnov test shows that own job-related general skills is equally distributed between sectors $(\mathrm{KS} = 0.0296;\ \mathrm{P} = 0.468)$. This is desirable, as it shows that the matching worked. Not unexpectedly, we find an unequal distribution of requested job-related general skills between LSH and F $(\mathrm{KS} = 0.1037;\ \mathrm{P} = 0.0000)$. Overall, the F industry requires less productivity from workers than LSH. However, this distributional difference between F and LSH is very small.

Figure 11: Kernel density of own ability scores by LSH employment (dotted line); and foreign industries (solid line). (Note: The Kolmogorov-Smirnov test points to equal distributions (chi=0.0424; P-value=0.506).

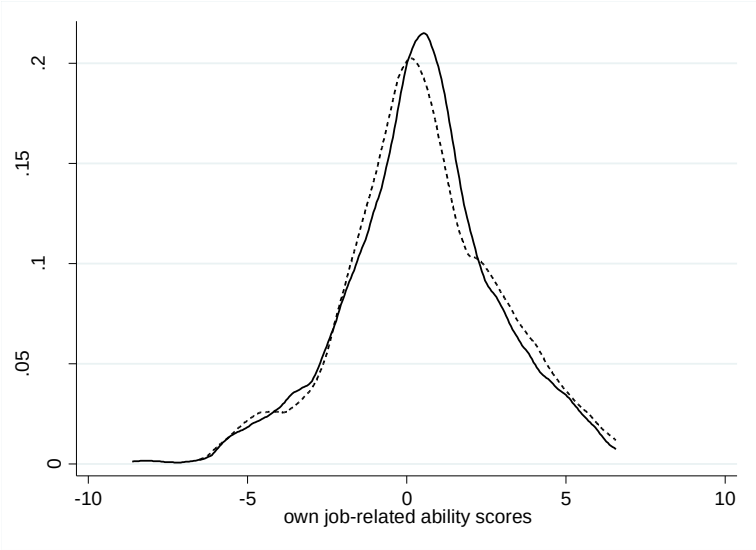
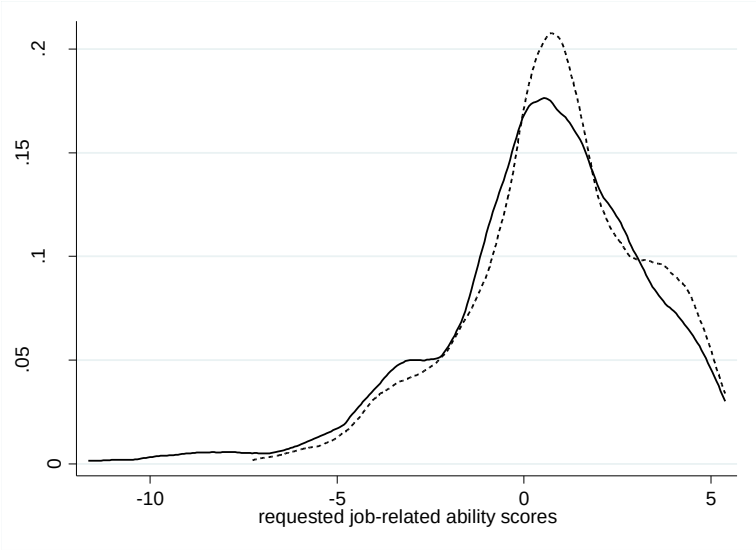


Figure 12: Kernel density of requested ability scores by LSH employment (dotted line); and foreign sectors (solid line). (Note: The Kolmogorov-Smirnov test points to unequal distributions (chi=0.0849; P-value=0.009).



8.2. Estimated wage differentials

The main results are summarized in Table 9. We present four subsequent models, namely: (1) wage differentials estimated by pooled ordinary least squares (pooled OLS[21]) without iterative one-to-one matching in Model 1; (2) wage differentials estimated by iterative one-to-one matching in Model 2; (3) wage differentials estimated for female nurses only; and (4) wage differentials estimated for female nurses only and controlled for seniority. Robust standard errors are presented between brackets. Each model is estimated by using regional fixed effects.

Table 9: Summary of estimation output (outcome variable = log wages)

	Model 1		Model 2		Model 3		Model 4	
Employment (F=1)	0.0311	**	0.0129		0.0038		-0.0163	
	(0.0149)		(0.0210)		(0.0226)		(0.0181)	
Requested ability	0.0029		0.0039		0.0004		0.0034	
	(0.0022)		(0.0047)		(0.0052)		(0.0037)	
Wage differential	0.0208	***	0.0214	***	0.0248	***	0.0164	***
	(0.0053)		(0.0073)		(0.0073)		(0.0060)	
Matching variables	-		Own abilities		Own abilities		Own abilities	
Control variables	None		None		Gender		Gender Seniority	
Specification	OLS		NNM		NNM		NNM	
Caliper			0.01		0.01		0.01	
Std.error	Cl(jcity)		Cl(jcity)		Cl(jcity)		Cl(jcity)	
	321		237		226		226	
Obs.	5,157		1,508		1,307 (Only women)		1,307 (Only women)	

Note: NNM denotes Nearest Neighbor Matching

[21] Note that the OLS estimates are pooled over the years 2003-2011.

First, consider briefly the results of the estimate of $\hat{\beta}$. The estimate of $\hat{\beta}_1$ is equal to +3.11 percent significant at 5 percent level in Model 1. This estimate drops to insignificant values once appropriately accounted for job-related ability in the other three models. Consider also the association between job-requested ability and log wages. We find that the estimate of $\hat{\gamma}$ is not significant and equal to +0.29 percent in Model 1. This finding is unchanged in the other models.

The estimate of interest is the inter-industry wage differential, namely parameter $\hat{\theta}$. In Model 1, the wage differential ($\hat{\theta}$=+2.08 percent) is significant at 1 percent level. Controlling for underlying differences with respect to job-related skills in the population between 'stayers' and 'switchers', the wage differential is equal to ($\hat{\theta}$=+2.14 percent) significant at 1 percent level in Model 2.

Next, we estimate the multivariate regression separately by gender. Therefore, we first drop the male nurses from the data, so that only female nurses are included in the multivariate regression. These results are visualized in Table 9, Model 3. The results for keeping only the male nurses are available upon request. For female nurses, the estimated wage differential $\hat{\theta}$ is equal to +2.48 percent significant at 1 percent level in Model 4. For male nurses, the estimated wage differential $\hat{\theta}$ is +1.21 percent and not significant. From this we may conclude that the wage differential, as estimated in the previous Model 2, is mainly driven by female nurses. However, note that owing to the small sample size of male nurses, this finding can be subject to a type-II statistical error, so that we may falsely accept the null hypothesis of no significant wage differential.

In Model 4, we additionally control for seniority by including the variable age in the multivariate regression.[22] The estimated wage differential $\hat{\theta}$ for female nurses drops to +1.51 percent, however, remains significant at 5 percent level. As such, seniority partially explains wage differences between stayers and leavers.

8.3. Industry mobility and non-monetary aspects of the nursing job

The results of the robustness checks are summarized in Table 10. Full model estimation output is available upon request. We provide four robustness checks in total for $\hat{\theta}$, the estimated wage differential.

[22] The estimate of age indicates that a one-year increase in age is associated with +1.65 percent higher wages.

Table 10: Summary of robustness checks (outcome variable = log wages)

	Model 5	Model 6	Model 7	Model 8
Employment (F=1)	-0.0211	0.0005	-0.0345	-0.03246
	(0.0163)	(0.0164)	(0.0299)	(0.0380)
Requested ability	0.0045	0.0065	0.0029	0.0003
	(0.0033)	(0.0036)	(0.0085)	(0.0086)
Wage differential	0.0144 **	0.0065	0.0214 **	0.0236 **
	(0.0056)	(0.0061)	(0.0118)	(0.0121)
Matching variables	Own abilities	Own abilities	Own abilities	Own abilities
Control variables	Seniority Characteristics Study program	Seniority Characteristics Study program Horizontal mobility	Seniority Characteristics Study program - Vertical mobility	Seniority Characteristics Study program - Vertical mobility Non-monetary
Specification	NNM	NNM	NNM	NNM
Caliper	0.01	0.01	0.01	0.01
Std.error	Cl(jcity)	Cl(jcity)	Cl(jcity)	Cl(jcity)
	237	213	167	155
Obs.	1,508	1,185	643	565

Note: NNM denotes Nearest Neighbor Matching

First, we control for gender, ethnicity, and study program information in Model 5. The influence of the variables `internship', `part-time program', and `dual program' on $\hat{\theta}$ may be particularly interesting. Geel et al. (2011) discuss that employers bear an increasing share of education and training costs the more specific the skills workers have to learn. As a result, apprenticeship training, for instance by interships, dual tracks or part-time programs, goes along with workers' occupational immotility (Geel et al., 2011). However, controlling for these variables does not capture the estimated wage differential ($\hat{\theta}$=+1.44 percent). These results are in line with Model 4 from Table 9.

Second, we classify individuals' switch as ‘vertical’ or ‘horizontal’ inter-industry mobility. It is in this respect that McGuinness and Sloane (2009) show substantial wage penalties for `over-education', for men and women, and for `over-skilling', for men only. In Model 6, we drop the data of all individuals who switched vertically, and then compare horizontally switchers to stayers. This is in contrast to Model 7, where we drop the data of all individuals who switched horizontally, and then compare vertically switchers to stayers. The results indicate that vertical mobility drives the estimated wage differential, as

$\hat{\theta}$ is not significantly different from zero in Model 6, whereas $\hat{\theta}$ is equal to +2.14 percent significant at 5 percent level in Model 7.

To conclude, in line with the critiques from Di Tommaso et al. (2009), we control for several other than monetary aspects of the job, namely: (1) type of contract; (2) the size of the organization wherein the individual works; (3) tasks of supervision; (4) whether the job has good career opportunities; (5) satisfaction with current work; and (6) information on the level of job (mis-)match. The estimate of $\hat{\theta}$ is still significant and equal to +2.36 percent significant at 5 percent level in Model 8.

9. Discussion and conclusions

This paper contributes to the previous literature on inter-industry wage differentials and job-related ability. We apply the skill-weights approach of Lazaer (2009) on the potential switch graduates in nursing can make from the life sciences and health industry to other, foreign industries, and estimate its effect on wages. The skill-weights approach argues that nurses will voluntary leave the LSH industry for a job outside LSH, in case seniority in LSH is lower than the returns to weighted general skills in other, foreign industries. The empirical strategy benefits from unique data on job-related general skills. These skills are the direct result of innate ability and individuals' background characteristics, on the one hand, and education in school and experience on-the-job, on the other hand. Owing to iterative one-to-one matching, we make graduates homogenous with respect to their background characteristics and abilities. The empirical strategy also deals with regional variation in employment opportunities in LSH.

The results from the estimated wage differentials are in line with the model predictions of Lazaer (2009): nurses who quit LSH earn, on average, higher (+2.14 percent) wages in other, foreign industries. Seniority can partially explain the estimated wage differential. The effect size is small, but can be supported by the elasticity of labor supply of nurses (Phillips, 1995; Askildsen et al., 2003; Shields, 2004; Di Tommaso et al., 2009). These results are driven by female nurses and by vertical industry mobility (i.e. `true' foreign industries), not by horizontal industry mobility. Non-monetary aspects of the nursing job do not capture the effect, so that we can conclude that our estimated inter-industry wage differential is robust to several model specifications and control variables.

This paper also provides valuable insights into the rise of recruitment bottlenecks in LSH by using the concept of market thickness. In general, risk-averse people will have the propensity to obtain a diploma that put high weights on learning skills vital for employment in the `thick markets'. In knowledge

societies, such as the Netherlands, thick markets arise for skill-intensive jobs, and recruitment bottlenecks are heavily associated with low end (industry-specific) vocational education or training (for a policy discussion on skill utilization in EU-27, see cedefop.europa.eu). The LSH industry behaves as a rather thin market. Studying health and welfare education or training largely involves the acquisition of industry-specific skills, and, to lesser extent, the acquisition of general skills (Hirsch and Schumacher, 2012). As individuals with nursing credentials cannot, or only to limited extent, apply their industry-specific skills in other than LSH industries, the potential switch a nurse can make directly implies the loss of suitability of industry-specific skills, and, consequently, the loss of investment in industry-specific education and training. The study, therefore, can be considered hazardous for people who are uncertain about the discounted value of health and welfare education or training.

Our findings, embedded in the skill-weights approach, also argue the chronic nature of recruitment bottlenecks in LSH. Seniority and skills' payoff are embedded in the industry structure, and, therefore, not easily to alter in the short run. The policy discussion in this respect is twofold: on the one hand, nurses are underpaid and unions are fighting for wage increase (for a discussion, see also Taylor, 2007). On the other hand, health care costs are rising and policymakers wish to cut costs also through freezing, or even lowering wages of health professionals. The LSH industry may well find its solution in the demand for informal care. Dutch policymakers already discuss the evolution from a `welfare state' to a `participation society', a society wherein every individual takes up its responsibility in caring for sick or senior family members or friends in order to cut in health care costs (King Willem-Alexander's speech from the throne, Prinsjesdag September 17th 2013, see rijksoverheid.nl). However, it is in this respect that Heitmueller and Inglis (2007) discuss substantial wage losses of informal care givers as a result of non-labor market participation.

Further research particularly dealing with horizontal industry mobility should focus on the extent to which nurses, who left the LSH industry, have an option to return to nursing. For instance, young graduates might need a few years to decide what the best occupation for them is. It should also focus on the decision to study health and welfare education or training in order to better understand the discrepancy between the perceived and actual discounted value of health and welfare education or training.

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Mismatch between Education and the Labour Market in the Netherlands: Is it a Reality or a Myth? – The Employers' Perspective

Melline Somers en Sofie Cabus

Abstract

This study examines whether the expansion in higher education over the past 20 years has contributed to better education-job matches on the labour market. In particular, we relate changes in the average formal schooling level of workers on the regional labour market to the educational attainment of the recruited staff within companies operating on that regional labour market. Hereby, it is acknowledged that companies most often recruit from a pool of workers available on the regional labour market. Next, we estimate the effects of changes in the level of schooling of the staff owing to the increased supply of higher educated graduates on the regional labour market on mismatch. Data from the Dutch Labour Demand Panel are used covering 7,451 unique companies over the period 1991-2011. The results indicate that a one-month increase in companies' workforce average schooling level decreases the probability that companies report mismatch with -3.0 percentage points.

Keywords: Education; Employer; Historical Trends; Mismatch; Skills

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1. Introduction

Many OECD countries have witnessed a continued rise in the supply of tertiary education graduates over the recent decades (Autor, Katz and Krueger, 1998; Goos, Manning and Salomons, 2009; OECD, 2014). The higher education expansion coincided with a significant increase in public investments in education and has raised several questions concerning its implications for the labour market (OECD, 2014). One of the consequences potentially brought forth by this expansion pertains to a mismatch between the skill supply and skill demand on the labour market. While various studies propose that the developments in higher education have resulted in an over-supply of college graduates (e.g., Di Pietro and Urwin, 2006; Hartog, 2000; Mason, 1996), ample evidence points out that the supply of high-skilled workers failed to keep pace with the demand for skilled labour (Bound and Johnson, 1992; Katz and Murphy, 1992). Conclusions on the labour market implications of the expansion in tertiary education therefore remain inconclusive and mostly limited to the perspective of employees (see e.g., Groot and Maassen van den Brink, 2000; McGuinness, 2006). Consequently, the overall picture we have on mismatch may be biased, or at least incomplete.

This paper provides a different perspective on the implications of the higher education expansion and examines whether employers have benefitted from the increased supply of high-skilled graduates. We explore how employers' perception on the (mis-) match between skill demand and skill supply within their companies has developed over the last two decades and link this to the educational attainment of companies' workforce. Our analyses are performed for the Netherlands that like most other OECD countries, has witnessed a growing number of enrolments in higher education as well as an increase in public expenses on education (van den Berge and ter Weel, 2015; CBS, 2011; Jacobs and Webbink, 2006; Leuven and Oosterbeek, 2000; OECD, 2014). Hence, the Netherlands provides an interesting case study to explore the consequences of the higher education expansion beyond the perspective of employees.

Only a small number of studies have attempted to evaluate the consequences of the increased supply of skilled labour from the perspective of employers (Belfield, 2010; Büchel, 2002; Kampelmann and Rycx, 2012; Tsang, 1987; Tsang, Rumberger and Levin, 1991). These studies have investigated through various approaches how firm productivity is affected by the presence of employees whose acquired level of education exceeds the required level for the job. One approach relies on standard human capital theory and derives productivity effects of over-education from workers' wages. This approach argues that over-qualified workers are more productive than their well-matched colleagues as over-educated workers generally receive a wage premium over their

adequately allocated colleagues (e.g., Groot and Maassen van den Brink, 2000; Rumberger, 1987). Other studies have examined the effect of over-education on productivity related factors such as job satisfaction and job turnover and found mixed results. While some studies found a negative relation between over-education and job satisfaction (Belfield, 2010; Hersch, 1991; Tsang, 1987; Verhaest and Omey, 2009), other studies did not find that over-educated workers report lower levels of job satisfaction in comparison to their well-matched colleagues (Büchel, 2002; Verhaest and Omey, 2006). Regarding job turnover, Hersch (1991) and Tsang, Rumberger and Levin (1991) provided evidence that the turnover rate is higher among over-qualified male workers, whereas Büchel (2002) indicated that over-educated workers show longer firm tenure than their adequately educated colleagues. Only a few studies attempted to estimate the impact of over-qualification on direct measures of firm productivity. Tsang (1987) showed that over-education is negatively and significantly related to job satisfaction which is in turn positively and significantly related to firm output. In contrast, a more recent study of Kampelmann and Rycx (2012) found that additional years of over-qualification have a positive effect on firm productivity.

The contribution of this study to the literature is at least twofold. Our study is the first to examine how the match between job requirements and employees' skills has developed over time according to employers. Doing so, this paper is also the first to provide a measure of mismatch that is based on employer-reports. The analyses are based on data from the Dutch Labour Demand Panel consisting of 11,817 observations from 7,451 unique companies between 1991 and 2011. Due to the richness of the collected data, this paper presents an overall and representative picture of mismatch from the employers' perspective.

The second contribution concerns our methodology. The composition of companies' workforce heavily relies on the endogenous recruitment process (Caldwell and O'Reilly, 1990). Due to endogeneity issues, direct estimates of the effect of an increase in formal education within companies on mismatch only allow for a correlational interpretation. However, prior research proposes that graduates' educational attainment on the regional labour market can be considered a public good for a company operating within that region (Moretti, 2004; Rauch, 1993; Tilak, 2008). An employer who seeks a good match with his vacancies heavily relies on the availability of workers in the area wherein business activities take place. In other words, the employer takes the worker availability within the regional labour market as given (i.e. exogenous), while the selection of workers into the company is endogenous. We take advantage of the consecutive steps an employer has to take to hire a worker (worker availability-recruitment-mismatch) by performing our analyses in two steps: (1) we relate the average formal schooling level of the regional labour force to the

average schooling level of the recruited staff within companies operating on that regional labour market; and (2) we estimate the effect of changes in the schooling level of the staff owing to the increase of high-educated graduates on the regional labour market on mismatch. This approach is similar to the instrumental variables method (Angrist, Imbens and Rubin, 1996). In this paper, individuals' educational attainment is defined as the total years in formal education. Given that we focus on the relation between the increased supply of skilled labour and the match between employees' skills and job requirements, our definition of educational attainment excludes other forms of human capital such as job training and work experience. However, we do consider other elements of individuals' educational attainment as an important direction for future research.[23]

The remainder of this paper proceeds as follows. Section 2 discusses the endogeneity issues regarding the educational composition of companies' workforce and addresses how we deal with those issues. Section 3 describes the data and presents descriptive statistics. The empirical framework is discussed in Section 4. Section 5 presents the results and Section 6 concludes.

2. Endogenous recruitment process

The educational composition of a company's workforce is determined endogenously owing to the recruitment process of the company. The selection of employees is not only based on the perceived match of employees' skills with the job requirements, but also with strategies that are heterogeneous across firms (Chatman, 1991). Firm characteristics that determine the educational composition of its workforce are often unobservable in empirical analyses and may pertain to human resource management strategies or specific skill needs. For instance, Bartel (1994) showed that workplace training is mostly received by high-educated workers and is more likely to take place in technologically progressive industries. Moreover, technologies can be skill complementary and favour certain type of workers (e.g., Autor, Katz and Krueger, 1998; Bartel and Lichtenberg, 1987; Machin and Van Reenen, 1998). Companies also decide whether to acquire certain skills and competences on the market or to develop them internally (Cappelli, 2008). Hence, companies sort themselves non-randomly into specific employee-company matches which, eventually, lead to different workforce compositions.

[23] One would also have to find additional valid instruments for job training and work experience in order to obtain unbiased estimates of the effects of these forms of educational attainment on mismatch. Based on the skill needs of the company, employers determine endogenously how much work experience their employees have through the recruitment process and how much and which types of training their employees should receive.

We exploit information on the average years in formal schooling of graduates available on the (regional) labour market to create exogenous variation in the average years in schooling attained by companies' employees. From the worker's perspective, employment opportunities mainly arise at the regional level due to restricted spatial flexibility (van Ham, Hooijmeijer and Mulder, 2001). The likelihood that employed individuals in the Netherlands search for another job or accept a job offer, increases with restricted commuting time (van Ommeren, Rietveld and Nijkamp, 1998). Therefore, companies are likely to draw their workforce from the pool of workers available on the regional labour market (van Ham, Hooijmeijer and Mulder, 2001). The empirical literature confirms that the job location is indeed one of the most important reasons for individuals to accept as well as to reject a job offer (Boswell, et al. 2003).

Moreover, we instrument the formal schooling of companies' workforce in time *t* with the formal schooling of the regional labour force in *t-1*. The timing of graduation and job arrival does often not occur simultaneously (van Ours and Ridder, 1992). Workers are heterogeneous in terms of the skills they possess and the skill requirements differ across firms (Pissarides, 2000). Furthermore, the location of the demand for certain skills does not always coincide with the location of the supply of these skills (Pissarides, 2000). Consequently, it takes time and other resources for a worker to find a good job with a good wage, and for a firm to find a proper match between a vacancy and a worker (Rogerson, Shimer and Wright, 2005; Stigler, 1962). Provided that labour markets do not clear automatically, changes in the composition of the labour force are reflected in changes in companies' workforce only after some amount of time.

The educational composition of the regional labour force can be treated as an exogenous supply of labour from the perspective of a single company as educational choices are made at the individual level (Moretti, 2004; Rauch, 1993; Tilak, 200). Early research already pointed at the economic theory that individuals make their human capital investment decisions according to their expected present value of education (Becker, 1964; Mincer, 1974). In addition, educational choices follow from information on the individual's ability, personality and occupational preferences (Holland, Gottfredson and Power, 1980; Weiss, 1972). Moreover, while our instrument is argued to be a good predictor of the endogenous regressor, it is unlikely to directly affect mismatch. Our outcome variable is derived from employers' perception on the degree to which employees adequately perform their job. The educational attainment of workers in the local labour force can only affect perceived mismatch if a company actually recruits workers from the regional labour market and reflects on the skills possessed by those workers. Hence, our instrument only indirectly influences mismatch through the endogenous recruitment process of the company.

However, considering the increase in the share of high-educated graduates in the Netherlands as exogenous to the company, we must exclude that companies select their location due to expected gains from available levels of human capital. This assumption implies that companies do not relocate to areas that supply the desirable levels of schooling according to their needs. Our data show that during the sample period almost 99 percent of the companies in our sample did not relocate (Section 3). Furthermore, the longer companies have been in a region, the less likely it becomes that those companies have been able to predict the supply of human capital in this region. As Section 5 will demonstrate, the results of our analyses remain unchanged once we account for location sorting behaviour.

3. Data and Descriptive Statistics

3.1. Labour Demand

The analyses are based on data from the Dutch Labour Demand Panel (Arbeidsvraagpanel) and the Dutch Labour Supply Panel (Arbeidsaanbodpanel) which are available at the Netherlands Institute for Social Research (scp.nl). The Labour Demand Panel survey is conducted biannually among Dutch employers and contains information on the composition of the workforce and employees' competencies. The dataset covers the period 1991 to 2011. On average, companies participated twice in the survey, yielding 33,601 observations. 26,530 Employers answered the question on mismatch which was formulated as: *'In your opinion, is your workforce sufficiently equipped to meet the job task requirements of the coming years?'* As from 2003, this question slightly changed to: *'In your opinion, is your workforce not sufficiently equipped to meet the job task requirements of the coming years?'* The answers were coded into a binary variable, taking the value '1' if the answer was 'mismatch, not sufficiently equipped', and '0' if the answer was 'no mismatch, sufficiently equipped'. [24] The mismatch question was not included in the year 1995.

17,498 Employers (52 percent) indicated the share of employees whose highest level of education fell into each of the following categories of Dutch diplomas: (1) university (WO) or higher professional education (HBO), (2) vocational education (MBO), general secondary education (HAVO) or pre-university education (VWO), (3) pre-vocational secondary education (VMBO), and (4) primary education. Based on the nominal study duration of each level of education, we translated the

[24] We test whether the parameter for mismatch on year is constant before and after 2003. The F statistic of the chow test for structural breaks yields 11.22 (p=0.000). Hence, we have to reject the hypothesis of stable coefficients. However, we do not observe any abrupt change in the mismatch pattern after 2001 and therefore conclude that the change in the mismatch question is not a concern.

educational attainment of companies' staff into average months as well as into years in formal schooling. After removing the observations with missing answers on the variables included in our analyses, our sample size is reduced to 11,817 observations (7,451 unique companies).[25] Table 1 shows that the average mismatch rate between 1991 and 2011 is 31.2 percent when no survey weights are used and 27.7 percent when survey weights are used. For the remaining analyses in this paper, the samples are always weighted in order to obtain a better representation of the population from which companies were drawn. The average years of schooling equals 13.4 years (or 160.5 months). A large pool of workers (32 percent VMBO; and 7.7 percent only primary education) would nowadays be classified as 'school dropouts', i.e., individuals without a secondary school-leaving certificate who are not in formal education.

Table 11: Summary statistics of the main variables

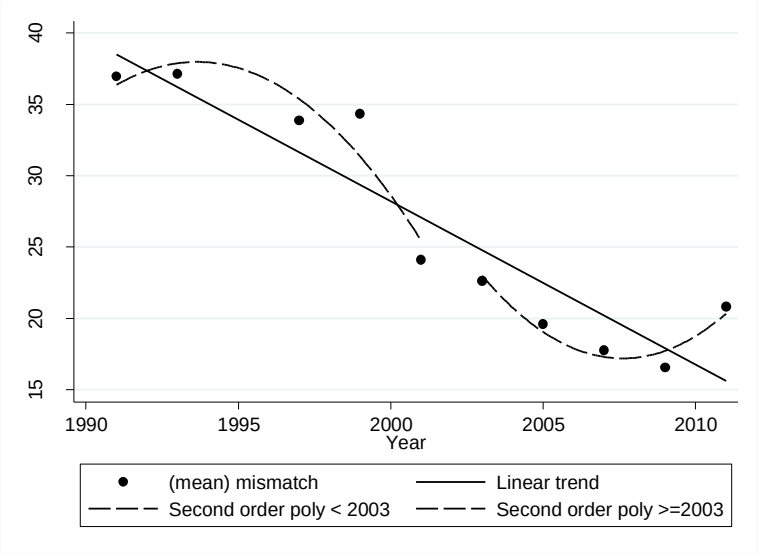
	N	Mean	Std.dev.	Min	Max
Mismatch					
mismatch (1=yes, 0=no) unweighted	11,817	0.3120	0.4630	0	1
mismatch (1=yes, 0=no) weighted	11,817	0.2770	0.4480	0	1
Highest educational level attained(1)					
Categories (%)					
WO; HBO	11,817	24.9	17.1	0	100
MBO; HAVO; VWO	11,817	35.4	30.3	0	100
VMBO	11,817	32.0	25.8	0	100
Primary education	11,817	7.7	29.8	0	100
Education (in years)	11,817	13.4	1.9	7	20
Education (in months)	11,817	160.5	23.0	86	243

Note 1: The categories denote: (1) university (WO) or higher professional education (HBO), (2) vocational education (MBO), general secondary education (HAVO) or pre-university education (VWO), (3) pre-vocational secondary education (VMBO), and (4) only primary education.

The mismatch rates for the period 1991-2011 are plotted on Figure 1. The linear trend shows that employers' view on the match between employees' skills and the job requirements significantly improved between 1991 and 2011. In 1991, almost 1 out of every 2 employers reported a degree of mismatch, while in 2011, only about 1 out of every 4 employers did so. There appears to be a cyclical pattern in the share of companies reporting mismatch. To observe this, we have fitted a second order polynomial function to the data and took 2003, when economic activity in the Netherlands was at its lowest point, as a breaking point.

[25] A two-sample t-test with equal variances indicates that the un-weighted mismatch rates of the full sample (32.18 percent mismatch) are highly comparable to the reduced sample (31.51 percent mismatch).

Figure 13: Employers' self-reported mismatch rates (weighted) 1991-2011



Employers' self-reported mismatch rates are also analysed per sector. While the downward sloping trend is observed for each sector in our dataset, the degree to which companies experience mismatch differs across sectors (Table 2). Whereas the transport sector has a historical low rate of mismatch equal to 18.0 percent, the education sector (36.7 percent), and the government sector (42.1 percent) have always been suffering from relatively high rates of mismatch. The downward sloping mismatch trend from 1991 to 2011 is relatively small for the government sector (-4.0 percent). Regarding the average years of schooling of companies' workforce, one could rank the 9 sectors from least attracting to most attracting (Table 3). The construction sector would be given rank 1, while the sectors industry and agriculture and transport receive second and third place. The education sector gets rank 9, followed by the sector business services and the government sector. The level of formal schooling increased for each sector, except for the sector other services.

3.2. Labour Supply

The Labour Supply Panel is biannually conducted and contains data on various aspects of the labour situation of employed and unemployed individuals aged between 16 and 66 years. On average, respondents participated three times in the survey. Questions typically deal with labour mobility, education and search behaviour for (other) jobs. The panel is used to construct the variable 'years and months in formal education on the regional labour market'. Between 1990 and 2010, 56,122 individuals were asked to report their highest attained level of formal education.

Table 2: Mismatch rates (weighted) 1991-2011 by sector

Sector	N	Mean	Std.dev.	1991	2011	Change (%)
Industry & agriculture	2,466	0.3202	0.4667	0.4060	0.2714	-0.3315
Construction	1,024	0.2199	0.4144	0.2786	0.1330	-0.5227
Trade, catering, repair	1,578	0.2113	0.4083	0.3338	0.1294	-0.6122
Transport	672	0.1798	0.3843	0.2229	0.1798	-0.1937
Business services	1,439	0.2573	0.4373	0.3390	0.1990	-0.4130
Life sciences & health	1,861	0.3429	0.4748	0.4582	0.2451	-0.4651
Other services	840	0.2217	0.4157	0.3172	0.1855	-0.4152
Government	829	0.4212	0.4940	0.4414	0.4236	-0.0404
Education	1,108	0.3668	0.4821	0.4668	0.3551	-0.2391

Table 3: Years in formal education 1991-2011 by sector

Sector	N	Mean	Std.dev.	1991	2011	Change (%)
Industry and agriculture	2,466	12.3	1.3	11.9	12.6	0.0605
Construction	1,024	12.1	1.3	11.8	12.6	0.0674
Trade, catering, repair	1,578	12.6	1.3	12.0	13.1	0.0919
Transport	672	12.3	1.5	12.0	12.7	0.0587
Business services	1,439	14.1	1.9	13.1	15.0	0.1430
Life sciences and health	1,861	13.8	1.6	13.3	14.3	0.0710
Other services	840	13.6	1.8	13.8	13.5	-0.0196
Government	829	14.0	1.4	13.1	14.5	0.1040
Education	1,108	16.5	1.1	16.3	16.5	0.0067

As discussed in Section 2, we will use the educational attainment of the local labour force in year *t-1*, to instrument for the educational attainment of companies' employees in year *t*. For each NUTS3[26] (in Dutch: COROP) region and for each year in our dataset we determined the average years/months individuals have been in formal schooling. There are 40 NUTS3 regions in the Netherlands, providing us 440 observations (i.e. 40 NUTS3 regions × 11 years). To obtain more information on how the educational attainment of men and women in the regional labour force relates to the human capital available within companies, we created two additional variables that distinguish between the formal schooling acquired by women and men.

Table 4 presents summary statistics of the educational attainment for the full sample. The educational composition of the labour force is plotted on Figure 2 by gender and by highest level of education attained. The average years in formal schooling of the labour supply equals 13.2. Figure 2

[26] The NUTS, the Nomenclature of Territorial Units for Statistics, is a geocode standard referencing the subdivisions of countries for statistical purposes. Depending on the size of the country, three levels of NUTS can be distinguished. Here, we use NUTS3 as a definition for the regions.

shows that a rising share of individuals has obtained a professional higher education- (HBO) or a university degree during the last two decades. Also the proportion of individuals obtaining a vocational education- (MBO), a general secondary education- (HAVO) or a pre-university education degree (VWO) has increased over time. Moreover, the share of individuals in the labour force with primary education as the highest attained level of education or school dropouts from secondary education (VMBO) has declined.

Table 4: Years in formal education on the regional labour market by gender (note: data collapsed by NUTS3 region and year)

	N	Mean	Std.dev.	Min	Max
All respondents					
Education (in years)	440	13.2	0.7	11.0	14.9
Education (in months)	440	158.1	8.9	132.0	178.3
Female respondents					
Education (in years)	440	13.0	0.8	10.3	14.9
Education (in months)	440	156.4	9.2	123.0	178.2
Male respondents					
Education (in years)	440	13.3	0.8	10.9	15.0
Education (in months)	440	159.8	9.5	130.5	180.3

Although the gap between men's and women's perspectives on the labour market has closed, there are still some notable gender differences. Figure 2 shows that between 1990 and 2010, about 27 percent of the male respondents acquired a university or professional higher education degree, compared to 22 percent of the female respondents. The largest gender differences are found for university education with completion rates of 8.2 percent for men and 4.7 percent for women. However, we observe a steep increase in the percent of women with a higher education degree, indicating that women are catching up. As from 1996, the share of women in the labour force without a secondary school-leaving certificate (i.e. school dropouts) declined from almost 45 percent to 26 percent in 2010.

3.3. Control Variables

Table 5 summarizes a set of control variables that may affect the likelihood that companies report mismatch. We account for workforce characteristics including the average age of companies' workforce and the type of contracts employees hold. We also control for company characteristics including the size of the company, the cyclical sensitivity and whether the company has a collective bargaining agreement. Finally we account for respondents job function, and for companies' location

sorting behaviour. To account for location sorting behaviour we include variables that deal with the year of start-up and with whether relocation took place during the sampling period.

Figure 14: Educational composition of women and men on the labour market 1990-2010

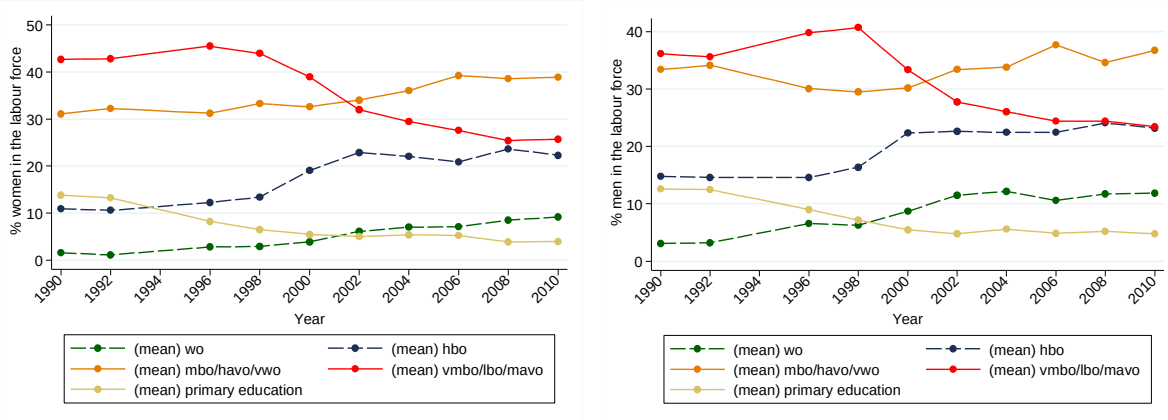


Table 5: Summary statistics of the control variables

	N	Mean	Std.dev.	Min	Max
Workforce characteristics					
Average age of employees	11,817	38.561	6.04	17.5	63.2
Employees with temporary contracts (1=yes, 0=no)	11,817	0.3866	0.4870	0	1
Company characteristics					
Company size					
0 - 19 employees	11,817	0.3790	0.485	0	1
20 - 49 employees	11,817	0.1970	0.398	0	1
50 - 99 employees	11,817	0.1380	0.345	0	1
100 - 199 employees	11,817	0.1400	0.347	0	1
> 200 employees	11,817	0.1460	0.353	0	1
Status of respondent					
Respondent is HR manager (1=yes, 0=no)	11,817	0.1890	0.3920	0	1
Respondent is HR officer (1=yes, 0=no)	11,817	0.0690	0.2540	0	1
Cyclical sensitivity					
Strong	11,817	0.2600	0.4390	0	1
Somewhat	11,817	0.3920	0.4880	0	1
Barely	11,817	0.3480	0.4760	0	1
Collective bargaining agreement (1=yes, 0=no)	11,665	0.8494	0.3577	0	1
Location sorting					
Company switched region (1=yes, 0=no)	11,817	0.0143	0.1187	0	1
Age company	10,829	30.278	29.508	0	600

4. Empirical Estimation

We estimate the effect of the human capital H_{ct} available to company *c* in year *t* on employers' perception on the match m_{ct} between skill demand and skill supply within the company. We then may write:

$$m_{ct} = \alpha_0 + \alpha_1 H_{ct} + \alpha_2 X_{ct} + \eta_r + \eta_s + \varepsilon_{ct} \qquad (1)$$

where m_{ct} is equal to 1 if company $c \in \{1,2,\dots,\mathrm{N}\}$ reports mismatch in year *t*, and 0 otherwise; X_{ct} constitutes a vector of company characteristics; η_r and η_s represent, respectively, region and sector fixed effects and ε_{ct} is the error term.

First, Equation (1) will be estimated by using a pooled ordinary least squares (OLS) regression without control variables (model a).[27] Subsequently, five extended regressions will be estimated by adding the available control variables in the following order: (b) average age of employees, (c) whether the company uses temporary contracts, (d) the size of the company and the job function of the respondent, (e) cyclical sensitivity and (f) whether the company is subject to a collective bargaining agreement, whether the company changed location during the sample period, and, the age of the company. The region and sector fixed effects specification will be used across all models to control for region- and sector-specific trends. All models cluster the standard errors at the level of the unique identification number of the company. Robust standard errors, controlling for heteroscedasticity, are presented.

Using pooled OLS estimation might yield biased estimates due to endogeneity. As discussed in Section 2, this paper addresses this endogeneity problem by instrumenting the educational composition of companies' workforce with the average schooling level of the regional labour force in a two-stage estimation approach. First, we estimate a regression using the endogenous regressor as the dependent variable, and the instrument as the independent variable. The first-stage regression can be written as follows:

$$H_{ct} = \beta_0 + \beta_3 HLF_{rt-1} + \beta_4 HLM_{rt-1} + \beta_2 X_{ct} + \eta_r + \eta_s + v_{ct} \qquad (2)$$

From Equation (2), fitted values $\widehat{H}_{ct}$ can be computed and plugged into the second-stage regression (see Equation (3)). While HLF_{rt-1} denotes the average years in formal schooling of female workers, HLM_{rt-1} represents the average years in formal schooling of male workers, both measured at the level of the regional labour market *r*. The second-stage regression estimates the effect of a one-

[27] According to Angrist and Pischke (2008), the OLS is as adequate as a probit or logit model, at least if the 'right' non-linear model is unknown.

month increase in companies' human capital stock that can only be explained by increasing the levels of formal education of men and/or women on the regional labour market, on mismatch. This effect is captured by the parameter α_1 in Equation (3).

$$m_{ct} = \alpha_0 + \alpha_1 \widehat{H}_{ct} + \alpha_2 X_{ct} + \eta_r + \eta_s + \varepsilon_{ct} \qquad (3)$$

5. Results

5.1. OLS Results

Table 6 presents the results of the pooled OLS regression as defined in Equation (1) of Section 4. The estimates with respect to companies' human capital stock (H_{ct}) are significantly negative in model (a) until (e). In model (e), the coefficient of interest gets closer to zero and in model (f) the coefficient loses significance.

Table 6: Results of the pooled OLS estimates (Equation 1)

y = mismatch m_{ct}	model1(a)	model1(b)	model1(c)	model1(d)	model1(e)	model1(f)
HC within company H_{ct}	-0.001**	-0.001**	-0.001***	-0.000**	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Control variables (1)	No	Yes	Yes	Yes	Yes	Yes
Number of clusters	7451	7451	7451	7451	7451	6760
Number of obs	11817	11817	11817	11817	11817	10686
adj. R^2	0.023	0.023	0.032	0.065	0.067	0.069

Note 1: The control variables are added in the following order: Average age employees (model b), labour flexibility (model c), company size and respondent's job function (model d), cyclical sensitivity (model e), location sorting and collective bargaining agreement (model f).
Note 2: All models account for region- and sector fixed effects. Standard errors clustered at the level of the company unit are in parentheses. Asterisks indicate significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

5.2. IV Results

5.2.1. First Stage Estimates

Table 7 presents the first-stage regression results as specified in Equation (2).[28] The human capital on the regional labour market has a positive relationship with the human capital within companies across all models. A one-month increase in the average months of education attained among female workers in the regional labour force in *t-1* is associated with a 0.222 months increase in the average months of schooling within companies in year *t*. For men, the estimated relation equals 0.154 months. The coefficient signs remain positive and significant after the inclusion of control variables. The educational attainment of women in the regional labour force appears to be a better predictor for the educational composition of companies' workforce. Working females commute less and are more likely to select a job location closer to their place of residence as they tend to put a higher value on time spent commuting due to household commitments (Turner and Niemeier, 1997). Moreover, as women are more often secondary wage earners than men, seeking to increase the family budget, they tend to look for a job with a more casual attitude (Kain, 1962).

Table 7: Results of the 1st-stage estimates (Equation 2)

y = HC within company H_{ct}	model2(a)	model2(b)	model2(c)	model2(d)	model2(e)	model2(f)
HC on labour market	0.222***	0.200***	0.181***	0.147***	0.147***	0.124***
Females HLF_{rt-1}	(0.051)	(0.052)	(0.051)	(0.051)	(0.051)	(0.052)
HC on labour market	0.154***	0.149***	0.143***	0.143***	0.143***	0.147***
Males HLM_{rt-1}	(0.021)	(0.052)	(0.051)	(0.051)	(0.051)	(0.051)
Controls variables(1)	No	Yes	Yes	Yes	Yes	Yes
Number of clusters	7451	7451	7451	7451	7451	6760
Number of obs	11817	11817	11817	11817	11817	10868
adj. R^2	0.446	0.447	0.452	0.458	0.458	0.467

Note 1: The control variables are added in the following order: Average age employees (model b), labour flexibility (model c), company size and respondent's job function (model d), cyclical sensitivity (model e), location sorting and collective bargaining agreement (model f).
Note 2: All models account for region- and sector fixed effects. Standard errors clustered at the level of the company unit are in parentheses. Asterisks indicate significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

[28] To confirm the validity of our instrument we have also computed under-identification tests, weak identifications tests and over-identification tests. The results are presented in Appendix 1. Based on the Kleibergen-Paap rank LM statistics we reject the null-hypothesis of under-identification. The obtained Cragg-Donald Wald F statistics indicate that we do not deal with problems of weak identification. Finally, the Hansen J statistics indicate that our instrument does not suffer from endogeneity problems.

5.2.2. Second Stage Estimates

The second-stage regression results of the analyses are presented in Table 8. Model (3f) shows that a one-month increase in employees' formal schooling reduces the probability that companies report mismatch with 3 percentage points (or -0.064 of one standard deviation). The coefficient of interest slightly increases in magnitude as we move from the basic model without control variables to model (3b). Model (3b) shows that companies with older employees are more likely to report mismatch, suggesting that older workers suffer from skill obsolescence which is not being offset by their job experience (De Grip and van Loo, 2002). Also companies using temporary contracts are less likely to report mismatch as such contracts allow companies to more easily lay off workers with inadequate skills. With respect to the company size, large sized companies are more likely to report mismatch in comparison to the smallest companies. Model (3d) also includes two variables indicating whether the respondent is either an HR manager or HR officer. As HR managers or HR officers are considered responsible for bringing about a proper worker-company match, their response on the mismatch question may be biased. However, the inclusion of these variables leaves the sign and significance level of the coefficient of interest unchanged. Model (3e) shows that compared to companies that are strongly sensitive to cyclical changes, companies that are hardly sensitive to changes in the economy are less likely to report mismatch. Hiring people with the appropriate skills becomes more difficult in times of economic growth, as the competition for labour becomes fiercer during such periods (Nickell, 1978). This especially holds for companies that are more sensitive to cyclical changes. Finally, model (3f) shows that our coefficient of interest remains negative and significant when controlling for whether companies are subject to a collective bargaining agreement and for companies' location sorting behaviour. Given that the share of employers reporting mismatch is rather dispersed across sectors (see Table 2), the results are most strongly driven by those sectors that have witnessed the greatest decline in the share of companies experiencing mismatch (see Section 3.1).

The pooled two-stage least squares estimator used to perform Equation (2) and (3) assumes that the effect of workers' educational attainment on mismatch is the same within each company. This assumption is only appropriate if company effects do not vary once we account for company and workforce characteristics. In the case that company effects are related to the educational composition of the company's workforce, variations in the effect of workers' formal schooling on mismatch need to be modelled in order to obtain unbiased estimates. We have performed Equation

(2) and (3) once more using the generalized two-stage least squares random-effects estimator.[29] The second-stage results can be found in Appendix 2 and are comparable to the results of the pooled regression models. We conclude that if company specific effects exist, they are not systematic but distributed randomly across firms. As such, the results of the pooled regression models can be considered robust.

6. Conclusion

Using a rich and unique dataset for the Netherlands, this study explored whether the increased supply of tertiary graduates has improved the match between skill supply and job requirements within companies. Whereas prior studies focussed on employees' perspective, we derived our measurement of mismatch from the perspective of employers. While almost 50 percent of the Dutch employers reported mismatch in 1991, in 2011, only 25 percent of the employers did so. Using a two-step empirical framework, we show that companies benefitted from an increased supply of skilled labour in the recent two decades. The first-stage estimates demonstrate that a one-month increase in formal schooling acquired by the regional labour force increases the educational attainment of companies' staff with almost 0.3 months. The second-stage results indicate that a one-month increase in companies' workforce average schooling level decreases companies' probability of experiencing mismatch with 3 percentage points. Our findings, therefore, show that firms have benefitted from the increasing supply of skilled labour.

Given that the Dutch college premium has continued to rise since the early nineties (van den Berge and ter Weel, 2015; Jacobs and Webbink, 2006; Leuven and Oosterbeek, 2000), our results could indicate that the supply of tertiary education graduates has responded positively to an increasing demand for skilled labour. In the case that the demand for skilled labour has indeed outpaced the supply of college graduates as the development of the college premium proposes, a declining mismatch trend would suggest that the value of an additional year of schooling has increased over time.

[29] In line with Clark and Linzer (2012), we prefer the random-effects specification over the fixed-effects specification as we have many units in our data (over 7000 unique companies), but few observations of each company (on average, each company appears twice in the data).

Table 8: Results of the 2nd-stage estimates (Equation 3)

y = mismatch m_{ct}	model3(a)	model3(b)	model3(c)	model3(d)	model3(e)	model3(f)
HC within company $\widehat{H}_{ct}$	-0.024***	-0.029***	-0.033***	-0.027***	-0.027***	-0.030***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
[HC within company $\widehat{H}_{ct}$,	[-0.052]***	[-0.061]***	[-0.070]***	[-0.058]***	[-0.057]***	[-0.064]***
mismatch standardized]	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)	(0.010)
Controls						
Average age employees		0.007***	0.009***	0.007***	0.007***	0.008***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Employees with temporary			-0.217***	-0.143***	-0.142***	-0.150***
contracts (1=yes, 0=no)			(0.022)	(0.023)	(0.023)	(0.026)
Company size						
0-19 employees				(.)	(.)	(.)
				(.)	(.)	(.)
20-49 employees				0.076***	0.075***	0.075***
				(0.021)	(0.021)	(0.023)
50-99 employees				0.035	0.034	0.028
				(0.030)	(0.030)	(0.033)
100-199 employees				0.097***	0.096***	0.121***
				(0.029)	(0.029)	(0.031)
> 200 employees				0.081**	0.080**	0.083**
				(0.038)	(0.037)	(0.041)
Respondent is HR manager				0.149***	0.147***	0.133***
(1=yes, 0=no)				(0.029)	(0.029)	(0.031)
Respondent is HR officer				0.118***	0.115***	0.101**
(1=yes, 0=no)				(0.036)	(0.036)	(0.040)
Cyclical sensitivity						
Strong					(.)	(.)
					(.)	(.)
Some					-0.019	-0.024
					(0.018)	(0.019)
Hardly any					-0.046**	-0.046**
					(0.020)	(0.022)
Collective bargaining						-0.231***
agreement (1=yes, 0=no)						(0.043)
Company switched region						0.280***
(1=yes, 0=no)						(0.092)
Age company						-0.001***
						(0.000)
Number of clusters	7451	7451	7451	7451	7451	6767
Number of obs	11817	11817	11817	11817	11817	10686
adj. R^2	0.047	0.049	0.061	0.083	0.084	0.082

Note 1: The control variables are added in the following order: Average age employees (model b), labour flexibility (model c), company size and respondent's job function (model d), cyclical sensitivity (model e), location sorting and collective bargaining agreement (model f).

Note 2: All models account for region- and sector fixed effects. Standard errors clustered at the level of the company unit are in parentheses. Asterisks indicate significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

However, the findings of our study could also mask a situation in which the presence of over-educated workers at the workplace has intensified over the past decades. Despite the increasing college premium, previous literature indicates that the increased number of high-skilled jobs has not been able to absorb the rising supply of skilled labour (Hartog, 2000; Muysken, Kiiver and Hoppe, 2003). Moreover, at current employment growth rates, the creation of high-skilled occupations is likely to fall behind the supply of high-skilled graduates in the next decade (Cedefop, 2014). As a consequence, job seekers can be forced to accept jobs below their level of education, at least in knowledge-based sectors. Provided that prior studies have illustrated that the presence of over-qualified employees can affect firm output adversely as well as beneficially (Büchel, 2002; Kampelmann and Rycx, 2012; Tsang, 1987), it remains unclear whether employers are willing or hesitant to hire over-educated workers. Hence, further research is needed to point out whether our findings merely reflect a rising incidence of over-education in the Dutch labour market.

While this paper focussed on the match between job requirements and the increased supply of tertiary graduates, the skills supplied by college graduates and therefore also the labour market prospects are heterogeneous across college majors (Machin and McNally, 2007). Hence, linking mismatch within companies to individuals' choice to enrol in a specific field of study provides interesting scope for future research. Future research could also explore how the observed mismatch trend relates to on-the-job training and the ability of school curricula to adjust to changing skill requirements.

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Appendix A: Tests for identification and instrument validity

	model(a)	model(b)	model(c)	model(d)	model(e)	model(f)
Under-identification						
Kleibergen-Paap rank LM statistic	152.707 (p<0.01)	118.504 (p<0.01)	102.254 (p<0.01)	79.039 (p<0.01)	78.643 (p<0.01)	64.566 (p<0.01)
Weak identification						
Cragg-Donald Wald F statistic	136.176 >	109.911 >	94.376 >	69.027 >	68.853 >	54.967 >
Stock Yogo threshold	19.93	19.93	19.93	19.93	19.93	19.93
Bias level	10%	10%	10%	10%	10%	10%
Over-identification						
Hansen's J statistic	0.318 (p=0.5726)	0.491 (p=0.4835)	0.649 (p=0.4204)	0.556 (p=0.4559)	0.643 (p=0.4228)	1.093 (p=0.2959)

Note 1: The control variables are added in the following order: Average age employees (model b), labour flexibility (model c), company size and respondent's job function (model d), cyclical sensitivity (model e), location sorting and collective bargaining agreement (model f).

Note 2: All models estimate NUTS3 region- and sector fixed effects. Standard errors clustered at the level of the company unit are in parentheses. Asterisks indicate significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Appendix B: Results of the second-stage estimates using a random effects specification (Equation 3)

y = mismatch m_{ct}	model3(a)	model3(b)	model3 (c)	model3(d)	model3 (e)	model3(f)
HC within company $\widehat{H}_{ct}$	-0.019***	-0.025***	-0.027***	-0.023***	-0.023***	-0.027***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Controls[a]	No	Yes	Yes	Yes	Yes	Yes
Dummies for COROP region and sector	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	11817	11817	11817	11817	11817	10868
Number of groups	7451	7451	7451	7451	7451	6760
R^2 within	0.001	0.001	0.000	0.000	0.000	0.000
R^2 between	0.005	0.005	0.006	0.014	0.014	0.011
R^2 overall	0.004	0.003	0.004	0.010	0.011	0.008
sigma u	.404	.510	.584	.511	.509	0.565
sigma e	.405	.409	.410	.413	.412	0.428
Rho	.499	.608	.670	.605	.605	0.636

Note 1: The control variables are added in the following order: Average age employees (model b), labour flexibility (model c), company size and respondent's job function (model d), cyclical sensitivity (model e), location sorting and collective bargaining agreement (model f).

Evidence Based Education and its Implications for Research and Data Analytics with an Application to the Overeducation Literature

Wim Groot en Henriëtte Maassen van den Brink

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1. Introduction

Our society is rapidly changing, is becoming more complex and diverse. This is also true for education. As a result of this, demands made on education have increased as well. Many of the most important challenges in life are thought to be best addressed through education. The Dutch essayist Karel van het Reve has pointed at the contradiction in our thinking about education. Many of us believe that educational standards and educational practice used to be better in the past than they are now, yet we cherish the belief in progress or, as Van het Reve puts it, "schools and all the other things are always becoming better and that mankind will be better off five hundred years from now."

The increased complexity and the rapid changes call for a further integration and application of scientific knowledge in educational practice. Teaching should become more 'evidence based' and questions on 'what works' in education should guide educational policy and practice more than they do now. This calls for a body of knowledge on the cost-effectiveness of educational interventions.
Evidence based education is the philosophy that education should be based on the best evidence about what works. This means that specific educational interventions, strategies and policy science should be evaluated before recommending or are introduced on a wide scale. If that has not happened yet these interventions should be introduced on an experimental basis, such that the effects of the intervention can be evaluated scientifically. Performance driven teaching includes some elements of evidence-based education such as working with measurable targets and systematically evaluating whether these objectives are met. However, the evidence-based approach is more than that. Evidence based education emphasizes the scientific basis to educational interventions. It is choosing a method or approach based on scientific knowledge about what works and it is the systematic scientific evaluation of whether the objectives are met.

Evidence based education emphasizes the investment nature of expenditures on education: education is an investment that yields a positive (and high) return for both individuals themselves and for society as a whole. With an investment approach the allocation of resources to interventions with a favorable cost-benefit ratio are socially profitable. This applies to any educational investment, but in particular for investments in young people from disadvantaged groups. Or, as Levin, Belfield, Muennig and Rouse (2006) have noted: "The investment criterion is a simple one: public investments are worth making if the benefits exceed the costs. Even if education is expensive, poor and inadequate education for substantial numbers of our young may have consequences that are even more costly. Such an analysis goes beyond the more basic question of social justice. If life

chances depend heavily on education, it is important that inequalities in education associated with race, gender, immigrant status, language, and handicap be redressed as a basis for equalizing opportunities in a democratic society. But, even beyond the issue of injustice is the question of whether a poor quality education has consequences for the larger society. Social science research shows that poor education imposes social burdens via lower incomes and economic growth, lower tax revenues, and higher costs of such public services as health, criminal justice, and public assistance. In this respect, it is possible to view efforts to improve educational outcomes for at-risk populations as a public investment that may have benefits for the entire society in excess of investment costs."

This chapter focuses in particular on the need for and implications of evidence based education. The discussion on evidence based education has much focussed on the attitudes and skills professionals require to work evidence based. For education to be evidence based teachers need to know how to use and apply knowledge about 'what works' in the classroom and policy makers need to apply it in educational policies. Much less attention has been paid to the supply side of this equation: how evidence based are the empirical findings offered by academic researchers? Evidence based education has two components: the systematic review of the existing evidence and the production of new evidence through the evaluation of interventions in experimental designs. This chapter focusses on the first component and raises the question how systematic the review of the evidence is that is presented in academic research? We do this by presenting a critical review of review studies. We ask ourselves how systematic these review studies have been conducted and how much these review studies have contributed to evidence based education. We apply this to the literature on the incidence and returns to overeducation in the labour market. Over the past 40 years there has been a prolific literature on overeducation. A simple search on 'overeducation' in Google Scholar yields nearly 200 studies with 'overeducation' in its title. Most of the studies on overeducation have been conducted by economists. This literature has been motivated by concerns about mismatch between skills supplied and skills demanded on the labour market, the concern that the education system educates too many people with a higher education degree and that these higher educated workers displace lower educated workers on the labour market. The outcome of these studies on overeducation can have important implications for education policy, most notably on policies to increase the number of higher educated people. As this literature is rather abundant, a number of review studies on this topic have been published over the years. As systematic review studies are an essential element in evidence based education, this enables us to assess how useful for evidence based education policy these reviews have been. It furthermore illustrates the potential contribution of the information gathered through data analytics to promote a more evidence based approach to

educational practice and policy.

The remainder of this chapter is divided in three sections. First we will make the case for evidence based education. Next we will assess whether the review studies on overeducation can contribute to evidence based educational policy making. Finally, we draw some conclusions.

2. The need for evidence based education

As a consequence of the above mentioned changes in society, the demands on education have changed. Education is no longer just about knowledge. Education is expected to contribute to socio-emotional development, is expected to prepare young people for citizenship and for the labor market, just to mention a few of the many things that are regarded as the tasks of education. Simultaneously, the student population has become more diverse: the diversity in the (ethnic) origin and the development of students has increased. Thus, the number of students with a disability - such as dyslexia or ADHD – that require remedial teaching and additional support has greatly increased. Teachers take the nature and development of their pupils more into account, and know that more can be achieved if they take the right approach to pupils. Finally, the importance of education has also increased. Knowledge is our most important production factor. The number of jobs for higher educated workers has increased, while employment of unskilled workers has declined. Harnessing talent is critical to a well-functioning economy and society. All this (and more) puts greater demands on education.

As a result of this there is a continuous discussion about education. Expectations about what education can achieve are sometimes unrealistically high. This has led to a call for more transparency and accountability of educational performance. Central testing of students and comparative international tests such as Pisa and Timms make the performance of schools and countries more transparent and make clear whether schools deliver what is expected of them. At the same time – as was clear from the quote from Karel van het Reve above – there is widespread dissatisfaction about the quality of education. This applies to all levels of education. The demand for greater transparancy and accountability of performance has been accompanied by the application of forms of ‘new public management’ in education. This has resulted in management on measurable targets. It has also led to an increase in bureaucracy and management in education. In recent years this has led to a backlash. The idea that managers have overpowered professionals has become common currency. A widely held view is that the quality of education would improve if teachers and lecturers are no longer bothered by rules and meddling managers and directors. Give education back to the teacher. Let the teacher again exercise his/her profession.

The claim that the quality of public services suffers from stifling rules and accountability procedures has also received support from scientists. In the Netherlands the Scientific Council of Government Policy (WRR) – a government think tank – in its report 'Evidence of Good Services' (‘Bewijzen van goede dienstverlening’) has argued for a revaluation of the 'professional (see: http://www.wrr.nl/content.jsp?objectid=2404). Accountability and management on measurable targets should – in the view of the think tank - be replaced by a culture of trust. Recognition of the value of the professional should, however, not take the form of an uncritical adoration. Greater freedom and autonomy for professionals goes together with a greater sense of responsibility.

Management and accountability are often depicted as organized distrust. Accountability, however, compels self-evaluation and, if well applied, contributes to better performance. Management and accountability are not organized distrust but should be the means to improve professionalism. The rejection of all forms of management and accountability is often nothing more than a call to be left alone and mind your own business. This usually does not contribute to better quality of education.

A greater reliance on and trust in professionals requires a strengthening of self-reflection among professionals. Do I still function properly as a teacher? Am I not stuck in my work? Human resource management, training and career counseling are often poorly developed in schools. Professionals often believe that they can take care of their own human resource development, but all too often this is lacking.

A professional attitude also requires that knowledge and skills are maintained and further developed. Continuous training is essential. The willingness of teachers to keep up with developments in their field and to participate in continuous training and development is sometimes lacking. Frequently there are no strict requirements about the amount of time teachers should spend on their own training and development. More stringent requirements for further training are therefore a prerequisite for the professional development of the teaching profession.

The developments outlined above are not unique to education: demands and expectations have increased in many areas of society, and with the increase in complexity the demands for transparency and accountability have increased as well. A response to the increased complexity and diversity in many sectors of society increasingly has been a stronger nexus between scientific knowledge and professional practice, and hence between knowledge institutions such as universities and the professional field. Data analytics can in part be seen as a response to this challenge. In the agricultural sector there is a strong link and collaboration between farms and agricultural universities and associated research institutes. In health care professional practice has become

almost completely based on evidence-based guidelines. Evidence based medicine has become the norm.

Compared to thirty or forty years ago, our society has also become more pragmatic and rational. The times of great ideologies that guide our daily living appear to be behind us. Indeed, ideologies and those who proclaim they are now found to be suspect. In western societies ideologies have been replaced by a belief in, and reliance on scientific knowledge.

There is another development which contributes to the importance of scientific knowledge in educational practice. That is the diminished authority of professionals. As indicated above society demands from professionals that they are accountable for their actions and behavior. Education is also expected to be accountable for the results it achieves. For teachers and educational administrators, this means more focus on performance by setting clear objectives and to examine systematically whether these objectives are met.

In its Education Report 2011, the Dutch Education Inspectorate qualifies performance driven teaching (‘opbrengst gericht werken’) as the main key to educational improvement. An analysis of Visscher and Ehren [5] show that performance driven teaching is mainly focused on the pursuit of three goals: teachers should set clear targets about what can be achieved in a week, a month or a year by a pupil, which approach or method that is most suitable to achieve this and knowledge to make use of the most effective methods and instruments. Performance driven teaching also requires data and the use of an evaluative cycle: defining goals and standards, collecting information, recording of the data, interpreting the data and decision making based on the information obtained by this. Data analytics can provide a valuable contribution to making education more evidence based.

Performance driven teaching can be seen as a form of evidence-based education. 'Evidence based education' refers to the idea that educational policy and practice should be based on the best available evidence of `what works’. It also refers to an evidence based *attitude* of policy makers and educational practitioners. Key to evidence based approach is that only those innovations and modernizations merit wider implementation and dissemination that are proven to be (cost-)effective. As long as such proof is not available, there should be ample room to experiment with these innovations and modernizations, as long as these experiments are accompanied by a sound scientific evaluation that enables an assessment of the causal impact of the interventions.

Despite its attractions, there is resistance against performance driven teaching and evidence-based education. This resistance is fueled by the contrast created between rationality and intuition. However, when taking the right decisions both kinds of knowledge – rational and intuitive – can be valuable. With an evidence-based approach a rational method is assumed. What is heard in the corridors, in the group, in the staff room as informal subjective information can be useful soft information. By gathering all relevant information and critically assessing the available evidence, better decisions are made. This dichotomy between rationality and intuition also exists between teaching and financial management in education. The allocation of the educational budget and the way we teach our students are closely related and mutually affect each other. Here again is a potential role for learning analytics to improve the efficiency in the relation between teaching and its outcomes and financial management of schools on the other hand. There is a lot to be gained here. Currently, cost-effectiveness analyzes are rarely or never performed in education. Contrary to other areas of in the public sector – like the health care sector and infrastructure where large research programs exist to increase the evidence base on the cost-effectiveness of investments in health care and infrastructure – there is no systematic attention being paid to generating evidence on the cost-effectiveness of interventions in education. The availability of data analytics again could be a stimulus to a research program on cost-effectiveness in education.

Whether we spend the money in education on the right things is a question that is indeed frequently asked, but is rarely studied systematically, let alone used in financial decision making in education. In school organizations, there is a wealth of information about cognitive performance and social and emotional development of students, there are good pupil tracking systems, there are parent, student and teacher satisfaction surveys. However, there is a lack of systematic analysis of the available data. Also the link between the goals and objectives in teaching and the financial management of the schools is rarely made. It must immediately be added to this that systematically linking the objectives of the teaching activities with financial management decision is not easy, but requires a systematic approach and sufficient skills and abilities of people involved to work evidence based.

In education, the gap between educational practice and educational science is still large. The use of scientific knowledge in educational practice is still uncommon. This is partly because the scientific research on education is not always useful for the practice. At both sides there are thus shortcomings: teachers do not know how scientific knowledge to find and use, researchers often study subjects that are not interesting and relevant for practice or do not bother to hand over their findings in accessible form to professional practice. Or they do not bother to present their work in a

way that contributes to evidence based education, as will be illustrated in the next section of this chapter.

The consequence of this gap between science and practice is that unproven practices in teaching can prevail. Or, as the journalist Carly Chynoweth has described the The Times in 2009: “Few patients would want doctors to make decisions based on their ideologies; when our health is at stake, we want to know that health professionals are drawing on evidence founded in rigorous scientific research. According to Sir Jim Rose, the former director of inspection at Ofsted, the education watchdog, and author of a government review of the primary school curriculum, the same should be true in education. “Very often [educational practices] take off much more from an ideology about how children learn rather than research,” he says. “That needs to be held up to the light”.” (Chynoweth 2009).

Knowledge about what works and what does not, keeps ideologies and unproven assumptions and beliefs outside the door. It makes teaching less vulnerable to what the British sociologist Frank Furedi has called the 'fetishization of change’, the assertion that we live in an era of unprecedented change and therefore every conceivable education reform is justified. Evidence based education offers a counterbalance against this 'fetishization of change’. Evidence based education not only establishes that teachers should be the primary agent of innovation in education, but also provides the professional knowledge and skills necessary to implement innovations that really improve the quality of education.

Some years ago, The Economist published a lengthy article on education reform under the title "The great schools revolution". The Economist identifies four factors that contribute to successful reforms: educational decentralization (giving power back to schools), extra attention for students with learning disadvantages, providing a choice of different types of schools and putting high demands on teachers. At least three of these factors come together in the development of evidence-based education: evidence-based education gives power over educational innovations and reforms to teachers and their schools. Schools that put evidence-based education into practice can distinguish themselves from other schools and if teachers work evidence based this improves the quality of teachers. This is also endorsed by the European Commission which stressed in 2006 that there is a need for a culture of evaluation and more systematic use of evidence as a basis for modernizing education and training systems.

Developing a body of evidence based interventions in teaching requires high quality research that is relevant for educational practice. Academic research on what works in education is not sufficient,

however. Knowledge about 'what works' needs to be disseminated to the teaching practice, i.e. to teachers. For this teachers needs to have the skills to interpret research results to make appropriate decisions in their teaching methods. Teachers who want to work evidence based must also themselves be able to conduct scientific research in their school and to implement the results of these scientific evaluated interventions in their school.

An evidence based approach also means that specific educational interventions, strategies and policies should be evaluated before being recommended or introduced on a wider scale. If that has not happened yet these interventions should be introduced on an experimental basis, such that the effects of the intervention can be evaluated scientifically. Evidence based education on the one hand refers to the set of interventions that have been positively evaluated, on the other hand it refers to an attitude of teachers and policymakers to work based on evidence-based education. Evidence based education emphasizes the scientific basis underlying educational interventions. From a normative perspective it gives preference to educational methods and approaches that are based on scientific knowledge about what works and it aims at the systematic scientific evaluation of whether the policy or teaching objectives have been met. An evidence-based approach to educational policy and practice is based on a judicious, explicit and rigorous use of current best evidence. An evidence-based attitude involves the teacher or the policymaker who is aware at every step of the decision process:

Whether there is evidence to support this decision;

How strong is this evidence?

An evidence-based attitude requires continuous scientific reflection on professional behavior. It assumes that interventions in educational practice or policy cannot be undertaken without consideration of the scientific evidence on this intervention and has as its goal that the choice of a particular intervention is based on the best available knowledge about the effectiveness of this intervention. The objective is to make use of the results of the research that uses the highest possible standards of scientific rigor. This preferably makes use of design based upon randomisation over treatment and control groups. An evidence-based teacher or policymaker is both a user and a developer of evidence based knowledge.

3. Overeducation and underemployment: what is the evidence base after forty years of research?

To meet the need and demand for evidence based education, an accessible supply of systematic reviews on 'what works' in education is necessary. However, researchers not always cater to the needs of educational professionals like teachers and policy makers, but frequently have their own agenda. Although in many fields – like medicine, psychology and educational sciences – well defined standards and guidelines for systematic review studies are available, these standards and guidelines are not always applied. In some disciplines – like in economics – these standards are also rather unknown and at least not imposed very stringently. This also becomes evident if – as is the purpose of this section – we review the review studies that have been published on overeducation – i.e. on the mismatch between skills supplied and demanded - in the economics literature.

Mismatch between supply and demand of skills on the labor market can take different forms. Vertical mismatch occurs if there are jobs for higher educated workers, whereas there are lower educated workers searching for jobs, or vice versa. Horizontal mismatch occurs if there are vacancies for some occupations or industries, while workers are (being) educated for other occupations and industries. Finally, there can be curriculum – job requirements mismatches: students are taught skills that are not needed or used in jobs or the skills and knowledge graduates need in their job are not taught at school or university. In this chapter we look at a specific form of vertical mismatch: overeducation. Workers are overeducated for their job if their education level is higher than the level required for the job. Overeducation may lead to displacement of lower educated workers by higher educated workers, where lower educated workers find that their chance of finding a suitable job diminish because higher educated workers enter into their jobs.

With the expansion of higher education the concern among academics and policy makers that workers may have become overeducated for their job that they perform has increased. On the other hand, the persistent finding that unemployment rates are higher among lower educated workers than among higher educated workers has raised the concern that higher educated workers are taking jobs intended for lower educated workers, leading to a displacement of lower by higher educated workers. This has focused attention to estimating the incidence of overeducation in the labor market. Overeducation may be inefficient and lower the returns to investments in education. Subsequently attention has been paid to estimating the rate of return to overeducation in the labor market.

The incidence and returns to overeducation have received attention from both economists and sociologists. Economists have more focused on overeducation, focusing on occupational mismatch – the mismatch between a worker's level of education and the level of education required for the job – and the waste in investments in human capital witnessed by the lower rate of returns to years of overeducation compared to the returns to years of education required for the job. Overeducation views the years of education the workers provides to the job relative to the educational requirements of that job. Sociologists, on the other hand, have focused more on inequities in access to the workplace by emphasizing the displacement of lower by higher educated workers and the underemployment of lower educated workers that results from that. McKee-Ryan & Harvey (2011) distinguish four perspectives on overeducation and underemployment: a focus on individual and organizational outcomes by management scholars, overeducation and their returns by economists, attention for the impact on society and social structures by sociologists and on health outcomes and community effects by community psychologists. Other perspectives can be added to this, like the attention to the effects on (job) satisfaction by scholars in happiness studies.

Although both the overeducation literature and the underemployment literature focus on the mismatch between demand and supply of skills, there is an important difference in emphasis between the two strands of the literature. Almost by definition overeducation is more likely to occur among higher educated workers as they have more opportunities and are more able to take up jobs with lower educational requirements. The underemployment literature on the other hand focuses more on the position of lower educated workers, as they are more likely to drop out of the labor market altogether and unemployment rates among lower educated workers are almost always higher than those among higher educated workers. Overeducation and underemployment may be related through a process of displacement of lower educated workers by higher educated workers. Higher educated workers displace lower educated workers to become overeducated in their job. Lower educated workers become unemployed or – in turn – displace even lower educated workers than themselves, if they find that all jobs which match their qualifications are already occupied. This process results in workers with the lowest educational attainment – who by definition are unable to displace lower educated workers than themselves – to become unemployed.

Underemployment emphasizes that workers cannot always fully employ the skills they have in their job. The sociological literature has also taken a somewhat broader perspective and has also looked at unemployment and at working part-time or fewer hours than desired as indicators of a mismatch between supply and demand for labor (for a more elaborate set of definitions of underemployment, see McKee-Ryan & Harvey 2011). Feldman (1996) distinguishes between five dimensions of

underemployment: being overeducated, being in a job outside one's area of formal training, having skills that are not utilized in one's job, working fewer hours than desired or being involuntarily in a temporary or intermittent job or earning 20% less than in one's previous job or as one's peers. In this view overeducation is only one of the perspectives on underemployment.

Studies on overeducation and underemployment have developed as two separate strands in the literature, the one dominated by economists the other by social scientists. In this chapter we treat them on an equal footing. Both strands of research - on the incidence and returns to overeducation and research on the rate at which lower educated workers are underemployed and displaced by higher educated workers – have turned into niches in the social sciences literature. Over the past forty years quite a few studies in these areas have appeared. A search in Econlit showed that at the beginning of 2015 there were 191 papers with 'overeducation' or 'over-education' in the title and 217 articles with the word 'underemployment' in the title. This proliferation of the literature on overeducation and underemployment literature has led to a number of studies that have reviewed the evidence on overeducation and underemployment. We count about a dozen studies that have summarized and reviewed the state of the art in these niche areas of research. The first study on overeducation – 'The over-educated American' by Richard Freeman – was published forty years ago in 1976 (Freeman 1976). The origins of the underemployment literature are ascribed by McKee-Ryan & Harvey (2011) to the seminal article by Feldman (1996), published twenty years ago. The existence of a number of review studies is evidence of the fact that research on overeducation and underemployment has matured during the past four decades and that a niche in the literature has grown into an established strand in research.

As is not uncommon in social sciences, research in both areas has developed quite independently of each other, without much cross-referencing or exchange of ideas and findings. Buchel (2001) is one of the few studies to relate overqualification/overeducation to un- and underemployment. According to him "The analogy between overqualification in general and unemployment lies in the fact that both are due to the aforementioned lack of demand for particular skills – with unemployment reflecting a total absence of demand and overqualification a shortfall in the volume of demand." He also observes that this analogy has received little attention in the academic literature so far.

This chapter aims to bring together these related but until now quite separate niches in the social sciences literature. It does so by providing an integrated review of the existing reviews of the research in the two areas. The aim of this review of reviews is to show how much this literature has contributed to evidence based education. We do so by focusing on the two main topics that provide

the motivation for research in this area. The first topic is: what can we learn from the literature about how pervasive overeducation and underemployment are in the labor market? Much of the research in this area originates from the concern that overeducation and underemployment is widespread and that the incidence of overeducation and underemployment is increasing. Directly related to this observation is the concern that overeducation and underemployment negatively impacts on the individual and on society. Overeducation and underemployment may carry a wage penalty, i.e. the rate of return to a year of overeducation is lower than the return to a year of education required for the job. These negative effects may be especially harmful if overeducation and underemployment are persistent and the negative effects of overeducation and underemployment continue to impact later on in the employment career.

Our review of reviews ignores methodological issues in estimating the incidence and the returns to overeducation. These issues have been satisfactory addressed by others elsewhere (see, f.e. Leuven & Oosterbeek 2011). Our focus is on the findings of the review studies rather than on the methodological discussion. We organize the discussion of the reviews around a few themes:

What is the incidence of overeducation/underemployment and is overeducation/underemployment increasing?
What are the returns to overeducation and how have the returns to overeducation evolved?
What are the causes of overeducation/underemployment?
Does overeducation lead to displacement of lower educated workers?

For our review of review studies on overeducation and underemployment we have identified papers in the literature on overeducation and underemployment that use a meta-perspective, i.e. studies that synthesize existing empirical studies, f.e. through a meta-analysis, and studies that describe the state of the art in this field. For our review of reviews, we searched Econlit and Google Scholar using as keywords: ‘review’, ‘overeducation’, ‘over-education’, ‘overschooling’, ‘overqualification’ and ‘underemployment’. We scrutinized the reference lists of the review studies in our initial search for any missing and additional studies that meet our inclusion and exclusion criteria.

The inclusion criterion is that the paper must represent a review of existing studies in the field and not original research. We exclude from our review of reviews studies that use primary empirical data and have as their primary aim to estimate the incidence of overeducation or underemployment, the rate of return to overeducation or other effects of overeducation or underemployment. Our search yielded 11 review studies published in academic journals and one book that are included in this paper.

Most of the review studies have been written by authors from the US, the United Kingdom and the Netherlands. This reflects the empirical studies in this field which are also primarily conducted in the US, the UK and the Netherlands (Kucel 2011). Some summarizing characteristics of the studies included can be found in table 10.1. The summary of findings in table 10.1 shows that most of the reviews are not systematic reviews, but rather a selective reading of the literature. Also a critical appraisal of the literature is very often lacking. As most of the studies are correlational studies using regression analysis to relate the incidence and the returns to overeducation to a number of observable characteristics, questions about the causal nature of the relation, the validity and the generalizability are highly relevant. However, very few of the review studies actually raise these questions. Furthermore, the main findings of the reviews are rather diverse.

Table 10.1 Characteristics of review studies included in the review

Author	Title – Reference	Objective	Number of studies and estimates included	Summary main findings
Smith (1986)	Overeducation and underemployment: an agnostic review, *Sociology of Education 59*, p. 85-99	Discussion of overeducation and underemployment	-	The increase in the number of higher educated seems to have had minimal impact on American society
Hartog (2000)	Over-education and earnings: where are we, where should we go?, *Economics of Education Review 19*, p. 131-147	Review of literature on incidence and returns to overeducation with emphasis on confrontation figures with theoretical models	-	There appears to be an asymmetry in the returns to overeducation and undereducation, as well in mobility and ability
Groot & Maassen van den Brink (2000)	Overeducation in the labor market: a meta-analysis, *Economics of Education Review 19*, p. 149-158	A meta-analysis of the estimates on the incidence and the returns to years of overeducation and education required	25 studies yielding 50 estimates on overeducation	Average incidence of overeducation is 23%, average rate of return to a year of overeducation is 3%. No evidence mismatch has increased.
Rubb (2003)	Overeducation in the labor market: a comment and re-analysis of a meta-analysis, *Economics of Education Review 22*, p. 621-629	Paper comments and expands meta-analysis of Groot & Maassen van den Brink (2000)	85 estimates on overeducation from 23 studies	Average return to year of overeducation is 5.2% and on year of education required 9.6%
Sloane (2003)	Much ado about nothing? What does the over-education literature really tell us?, in: Overeducation in Europe: Current Issues in Theory and Policy	Paper reviews the literature on a number of issues on overeducation	-	There is support for the substitutability hypothesis where overeduction is substitute for lack of other human capital. Whether overeducated workers crowd out lower educated workers is far from clear, but for large group of workers overeducation is a permanent rather than a temporary feature.
McGuinness (2006)	Overeducation in the labour market, *Review of Economic Surveys 20*, p. 387-418	A review of the literature on overeducation and assessment of findings with theoretical frameworks	33 studies generating 62 estimates on overeducation	The impact of overeducation is non-trivial and potentially costly to individuals and society
Kucel (2011)	Literature survey of the incidence of over-education: a sociological	Main objective is a review of the incidence of overeducation covering	52	Overeducation is not a negligible problem that affects only a minority of workers. The incidence of overeducation has

	approach, *Reis 134*, p. 125-142	the period 1983-2009		increased considerably over time in various countries
Leuven & Oosterbeek (2011)	Overeducation and mismatch in the labor market, Discussion paper series, Forschungsinstitut zu Zukunft der Arbeit, No 5523	Survey of the economics literature on overeducation	42	Estimates of the returns to overeducation may suffer from omitted variable bias and measurement error
McKee-Ryan & Harvey (2011)	"I have a job, but …": A review of underemployment, *Journal of Management 37*, p. 962-996	Survey of literature on underemployment and their effects	-	Recessions increase underemployment and an increasing number of workers will face underemployment during their career
Scurry & Blenkinsopp (2011)	Under-employment among recent graduates: a review of the literature, *Personnel Review 40*, p. 643-660	What is underemployment under recent graduates	-	Individual volition and meaning making are important issues that remain under-researched in relation to graduate underemployment

The incidence and evolution of overeducation and underemployment

The oldest review of the overeducation and underemployment literature is Smith (1986). This review is focused on college graduates in the US and reviews the literature of the 1970s and trends in the supply and demand for college graduates for the period 1947-1982. Smith (1986) concludes from his reading of the literature that overeducation/underemployment of college graduates has had no effect on college enrollment and that despite the concerns about the social waste of overeducation/underemployment it remains unclear whether it really constitutes a social problem. What appears from this review – and what has been corroborated in subsequent reviews – is that the frequently pessimistic predictions that overeducation has increased or will increase in the future, that the rate of return to education will decline and that the overeducation has a scarring effect on workers which they will carry with them for the rest of their career, is not supported by the evidence and has not materialized. These pessimistic predictions are mainly based upon demographic changes: the idea that the large birth cohorts after the Second World War and the increased enrollment in higher education would lead to an oversupply of college graduates and when the increase in the demand for high skilled workers would slow down, result in overeducation/underemployment. But, as stated by Smith in 1986: "(…) the grim forecasts of the mid-1970s have not come true." It seems that Smith is a bit confused by the belief that overeducation is increasing and the value of a college degree is declining on the one hand, and the figures which do not quite support these beliefs on the other.

Fourteen years after the review by Smith (1986) two new reviews were published. One was a narrative review of the literature (Hartog 2000), the other a meta-analysis on the incidence and returns to overeducation (Groot & Maassen van den Brink 2000). These reviews distinguish between three different ways of measuring overeducation. These are described by Hartog (2000) as (1) the systematic job analysis method, where for each job title the required level of education is determined, (2) the self-assessment method, where workers indicate what education is required for the work they do, and (3) the realized matches method, where the required level of education is derived from the mean or mode of the actual education level of workers in a job. Leuven & Oosterbeek (2011) provide a more detailed and richer classification of the measurement of overeducation, although their measures of overeducation can also be grouped in the three described by Hartog (2000). As argued by Hartog (2000) each of the three methods has it attractions and limitations. However, the job analysis method is identified by Hartog (2000) as the best and the conceptually superior method, as it produces the least bias in the measurement of overeducation. Groot & Maassen van den Brink (2000) show that of these three measures, the first – the job

analysis method – generally provides the highest estimate of overeducation, while the realized matches method yields the lowest estimates of overeducation. The incidence of overeducation based on the self-assessment method is similar to the job analysis method. On average the job analysis method yields an estimate of the incidence of overeducation which is approximately twice as high as the realized matches method. McGuinness (2006) draws a similar conclusion, although with smaller differences: he finds that that the objective measures of overeducation indicate an incidence of overeducation which is about a quarter less than the subjective measures.

Reviews that address the incidence of overeducation frequently come to the conclusion that the incidence of overeducation is high. Kucel (2011) claims that between a quarter and a third of the workers in advanced economies are overeducated for the work they do. This is similar to what Leuven & Oosterbeek (2011) find: the mean and median incidence in the studies in their review is 30%. Groot & Maassen van den Brink (2000) – although including a smaller number of studies on the incidence of overeducation for a more limited time period – find an average incidence of overeducation of 23%. The common conclusion of these review papers is that the estimates of the incidence of overeducation vary and that the incidence of overeducation is generally estimated to be high but depends on the way it is measured.

Scurry & Blenkinsopp (2011) use a classification developed by Feldman (1996) which defines a person as underemployed if (s)he:

> Possesses more formal education than their job requires;
> Are involuntary employed in a different field from that in which they received their formal education;
> Possesses higher-level skills than the job requires;
> Are involuntarily engaged in part-time, temporary or intermittent employment;
> Are earning 20 percent less than the average earnings of their graduating cohort in the same major or occupation track.

As the above definition shows, underemployment is a much broader and diffuse concept than overeducation. Because of that exact figures on the incidence and extent of underemployment are scarce. McKee-Ryan & Harvey (2011) state that the incidence of underemployment in the US ranges from 17% to a third of the workforce, depending on what is included in the definition of underemployment. As with the estimates of overeducation, there is substantial diversity in the estimates of underemployment.

A frequently asked question is whether the incidence of overeducation is increasing or not? The reviews included in this review provide diverging answers to this. According to Kucel (2011) a review of 52 studies on the incidence of overeducation shows that "…. over-education is not a negligible problem affecting only a minority of the labor force, and that its incidence has increased considerably across time for various countries." Unfortunately, Kucel (2011) provides no statistical tests for an increasing trend in overeducation. McKee-Ryan & Harvey (2011) also conclude that "(…) the number of underemployed workers continues to rise", but do not provide figures to substantiate this claim.

Hartog (2000) comes to a somewhat similar conclusion. He concludes that for the three countries – the Netherlands, Spain and Portugal - for which he has comparable data over time, the incidence of overeducation has increased has increased during the period 1970-1995. For the US, he concludes that overeducation followed a U-shaped pattern between 1969 and 1977, but that overeducation decreased between 1977 and 1984. Leuven & Oosterbeek (2011) come to the somewhat similar conclusion that overeducation declined from the 1970s to the 1990s. They also find that overeducation increased in the 2000s.

Slightly different conclusion are drawn by Groot & Maassen van den Brink (2000) and McGuinness (2006). Groot & Maassen van den Brink (2000) find in a regression analysis on 50 estimates of the incidence of overeducation taken from 25 studies no statistically significant differences in the incidence of overeducation between the 1970s, 1980s and the 1990s. This conclusion is confirmed by McGuinness (2006) who observes that the incidence of overeducation has been rather stable over time.

Fluctuations in the incidence of overeducation can be explained by business cycle fluctuations and by skill-based technological change. Groot & Maassen van den Brink (2000) account for that by including the growth in the labor force and the unemployment rate for the year in which the data on the incidence of overeducation were gathered in a meta-regression on the incidence of overeducation. They find no effect of the unemployment rate on the incidence of overeducation, but they do find that a one percentage point higher growth of the labor force increases the incidence of overeducation by about two percentage points. However, McKee-Ryan & Harvey (2011) conclude that economically or personally difficult situations or – as they call it – 'facing challenging conditions' increase the likelihood of underemployment.

In general the reviews conclude that the incidence of overeducation is high, although the estimated incidence of overeducation widely differs between studies. Many of the reviews also argue that the

incidence of overeducation is rising. The high incidence of overeducation raises questions: what does the high incidence rate of overeducated workers mean? Does it indicate widely prevalent mismatches on the labor market. The high incidence in combination with an alleged increase in overeducation suggests a labor market that is greatly distorted. Alternatively, we may doubt the validity and reliability of the measurement of overeducation. According to Sloane (2003) "…. It seems clear that a substantial part of what is referred to in the literature as over-education simply reflects the heterogeneity of individual abilities and skills within particular educational qualifications."

The returns to overeducation and underemployment

Smith (1986) argues that the human capital theory fails to explain why people go to college, despite the increase in overeducation and the decline in the rate of return to the investment in human capital that results from it. The figures presented in Smith (1986) seem to suggest that the ratio of mean earnings of college graduates to those of high school graduates in the US declined in the 1960s. This decline was reversed somewhere around 1974. As Smith (1986) reports the college earnings premium continued to increase through 1983. This finding is corroborated and extended by the meta-analysis of the returns to education in Groot & Maassen van den Brink (2000). They find that the rate of return to a year of education required was 4 percentage points higher in studies using data for the 1990s than in studies with data for the 1970s. The rate of return to a year of overeducation was 2.4 percentage points higher in studies for the 1990s than in the 1970s, although this effect was not statistically significant. McGuinness (2006) concludes in his review of studies on the returns on overeducation that the three approaches used to measure overeducation – the job analysis method, the self-assessment method and the realized matches method – "generate broadly consistent evidence" on the returns to overeducation. In a re-analyses of the meta-analysis in Groot & Maassen van den Brink, Rubb (2003) finds that the rate of return to a year of education required was 2.59 percentage points higher studies with data for the 1980s and 3.98 percentage points higher in studies for the 1990s than in studies using data for the 1970s. For the rate of return to a year of overeducation, he finds that the rate of return to a year of overeducation was 2.88 percentage points higher in the 1980s and 1.79 percentage points higher in the 1990s than in the 1970s. Both meta-analyses clearly show the rising trend in the return to education since the 1970s.

The third and most recent meta-analysis on the returns to (over)education – aside from Groot & Maassen van den Brink (2000) and Rubb (2003) – is Leuven & Oosterbeek (2011). They find in their meta-analyses of returns somewhat larger differences between the rate of return to a year of education required and a year of overeducation. They find that on average the return to a year of

education required is around 9% and the return to a year of overeducation is about half of that. They do not observe a systematic pattern in the rates of return to education over time, only during the 1990s returns to a year of overeducation appear to be somewhat lower (-1.5%) than in studies that use data for the 2000s. Somewhat contradictory, the rate of return to a year of education required is 1.8% higher during that same period in the studies in their sample. They further find that in the 1980s the rate of return to a year of education required is 1.4% lower than in studies using data for the 2000s. The latter also suggests an increase in the return to years of education required.

If we compare the returns to overeducation in the review of Leuven & Oosterbeek (2011) with those in Groot & Maassen van den Brink (2000) and Rubb (2003), those in former review appears to be larger than those in the latter two reviews. Leuven & Oosterbeek (2011) also find a higher rate of return to a year of education required than Groot & Maassen van den Brink (2000) and Rubb (2003). This is consistent with an increasing trend in the returns to education since the 1970s due to the demand for higher educated workers outpacing demand.

It is interesting to note that both the meta-analysis of Groot & Maassen van den Brink (2000) and that of Leuven & Oosterbeek (2011) find that the way that overeducation is defined and measured has a great impact on the reported incidence of overeducation (with the measure with the highest incidence identifying about twice as many workers as overeducated as the measure with the lowest incidence), but that there are no statistically significant differences in the rates of return to a year of overeducation and a year of education required between the different methods to measure skill mismatches.

Hartog (2000) observes that the estimates on the rates of return show that undereducation is less severely punished than overeducation is rewarded. From this he concludes that the more able workers are found among the undereducated, while the abilities and skills of the overeducated do not differ from those of workers who are correctly allocated. Taking this conclusion a step further it seems that workers who are undereducated attain position on the labor market based on their abilities and despite their (lower) education level, while overeducation seems to be more the result of chance or lack of luck in finding the right job or not.

Underemployment also has negative wage effects. McKee-Ryan & Harvey (2011) report wage losses after a spell of unemployment of 14% to 35% per year. They also specify a range of other areas such as job satisfaction, organizational commitment and well-being on which underemployment has a negative impact. Other reviews come to more qualitative conclusions on the returns to overeducation. According to Sloane (2003) "… over-education has long-run as well as short-run

effects on wages. There appear to be scarring effects for those workers who do not obtain a good match early on in their careers."

What are the causes of overeducation and the lower returns to overeducation?

Overeducation can be seen as an indicator of mismatch between skills supplied and demanded on the labor market. The lower rate of return to a year of overeducation relative to a year of education required is then informative about the efficiency losses of this mismatch. However, other interpretations of overeducation are also possible. Overeducation may indicate lower abilities or a lack of other aspects of human capital. One of the arguments in Groot & Maassen van den Brink (2000) is that overeducation can – at least partly – be explained as a substitute for the lack of other elements of human capital such as on-the-job experience and training. They support this argument by noting that workers with less other forms of human capital (like tenure, experience and on-the-job training) and workers with career interruptions (like unemployment spells and spells out of the labor market or working part-time) are more likely to be overeducated. Sloane (2003) also concludes that formal education is one aspect of human capital and education deficits can be remedied by other aspects of human capital, such as on-the-job training. Alternatively overeducated workers may be more attractive for employers as they need lees on-the-job training.

McGuinness (2006) relates this theory of overeducation as a compensation for a lack of work-related human capital to the permanent or temporary nature of overeducation. If the compensation theory is correct, overeducation may decrease as workers accumulate more tenure and experience over time. McGuinness (2006) notes, however, that it is unclear to what extent the trade-off between education and experience is the result of human capital substitution or cohort effects. As noted by Kucel (2011) overeducation is only consistent with human capital theory if overeducation is temporary and compensates for lack of other skills such as experience or (on-the-job) training.

The alternative line of reasoning views overeducation as the result of labor market inflexibility and 'bad luck'. In this argument – first put forward by Thurow (1975) – there are only a limited number of jobs for higher educated workers. With an excess supply of higher educated workers, some of them fail to find a job that matches their skills and have to do with a lower skilled job for which they are overeducated, thereby displacing lower educated workers who may fall out altogether and face unemployment. Education is here seen as a way to get ahead in the queue for the best available jobs. Overeducation, in this view, is the result of an excess supply of higher educated workers. Some support for this claim is found in Groot & Maassen van den Brink (2000).

Does overeducation lead to displacement of lower educated workers?

Overeducated workers may displace lower educated. However, overeducation does not necessarily affect the labor market position of lower educated workers. If there is an oversupply of higher educated workers but a shortage of workers for lower educated jobs, overeducation may be a way to balance supply and demand for lower and higher skilled workers and jobs. According to Scurry & Blenkinsopp (2011) there are three explanations for underemployment. The first is similar to the compensation argument for overeducation and says that underemployment can be a temporary period used to acquire additional skills and experience, a stepping stone to a better fitting job or to cover a period before career decisions are made. The other explanation is that underemployment is a way to avoid unemployment. The third explanation they offer is that underemployment is part of a lifestyle choice. While these explanations focus on why individuals may end up in a job for which they are overeducated or underemployed, others have looked at the implications of overeducation. An issue that has attracted attention both in the academic and the popular literature is whether overeducated workers displace or crowd out lower educated workers. Especially if overeducation is a long-term state of affairs, overeducated workers may crowd out lower educated workers. Sloane (2003) provides a review of the academic literature on this issue and concludes that "…. the evidence for crowding out is rather thin, being limited to outflows rather than inflows of workers with relatively low levels of education."

Whether overeduction leads to a crowding out of lower educated workers depends – among others – on the incidence and persistence of overeducation. The higher the incidence and the greater the persistence, the more overeducation will crowd out lower educated workers. Above we have addressed the incidence of overeducation, here we focus on the evidence on its persistence. Are many workers temporarily overeducated for the work they sometime during their career or are some workers permanently in a job for which they are overeducated? The studies reviewed by Sloane (2003) do not seem to provide an unequivocal answer to this question. Sloane (2003) therefore comes to the somewhat unsatisfactory conclusion that more research is needed using panel data with direct questions on overeducation. Leuven & Oosterbeek (2011) come to more specific conclusions and claim that "various studies corroborate that for many workers overschooling persists." Unfortunately they do not provide figures to support this claim.

4. Conclusion

In many areas there already exists a strong nexus between scientific knowledge and professional practice, and thus between knowledge institutions such as universities and the professional field. In the agricultural sector is a close link between farms and agricultural research. In health care, evidence-based medicine has become the standard. It might be good to note that work in evidence-based medicine is only recent. The term itself has only become commonplace since the early 1990s. In many areas in medicine is still very little or no scientific evidence, but in the areas where this is the case, evidence-based medicine is widely accepted and has become the standard of practice. Much of the evidence is also put into guidelines to which physicians are expected to adhere. Meanwhile, in nursing, social work, psychotherapy, occupational therapy, physiotherapy and speech therapy the evidence-based approach is widely embraced and accepted.

A doctor who does not adhere to the scientific guidelines for treatment based on evidence based medicine is likely to face disciplinary charges and risks losing his/her license to operate. Rightly so. A doctor who does not work according to the best available knowledge, can do much harm to patients. But the same can be said for a teacher. A teacher who does not use effective teaching methods can do much harm to children as well. A poor education can have lifelong negative effects. A bad teacher can be worse than a bad doctor as a bad teacher may be harmful from a young age onwards until the end of one's life. As education has an effect on many areas in life – ranging from one's income to one's health – the damage done by a bad education can be far more extensive. Research by Peter Tymms et. al (2009) shows that having a bad teacher at the beginning of one's educational career can have lasting effects. The negative effects of a bad teacher in the first grade of primary school are still discernable in the eighth grade.

Education is still very much based on ideology rather than science. Teachers, like doctors, should work on the basis of the best available knowledge about 'what works'.

To enable teachers or policy makers to work evidence based, academic researchers should supply them with systematic information and knowledge about 'what works' in education. Especially in the economic science, but also in the social sciences at large, there is a lack of systematic evidence on what works. In this chapter we have illustrated this by critically reviewing the review studies on overeducation and underemployment. Overeducation and underemployment are topics that have received considerable attention from academic researchers over the past forty years. This attention mostly originates from a policy perspective: the notion that overeducation and underemployment imply a waste of talent and resources. Over the past sixty years the educational attainment of the

labor force has increased dramatically. In many countries enrollment in higher education has increased tenfold during this period. This has raised concerns about overeducation of the workforce. As described above, many studies on the incidence of overeducation and underemployment have supported the idea that overeducation is a result of the increased educational attainment of the labor force. This suggests that the increase in educational attainment has come at the cost of the overeducated worker. As noted by Tinbergen (1975), the rate of return to education is determined by the race between demand and supply of skills. If we look at the literature on the rate of return to education, we can conclude that during the past four decades this race has been won by the supply side. The literature on the rate of return to education shows that in virtually all western countries the rate of return to a year of education has increased (cf. Groot & Maassen van den Brink 2000 and Leuven & Oosterbeek 2011), suggesting that the because of technological changes the demand curve has shifted outward, leading to a higher rate of return even as the supply of higher educated workers has increased. There seems to be a discrepancy between the overeducation literature which raises concern about the consequences of the increase in educational attainment and the literature on the rate of return to education which suggests that because of the more rapid increase in the demand for educated workers, income inequality between lower and higher educated workers has increased. As the policy relevance of the topic is high, it is important to know whether the academic research provide any useful tools for evidence based policy making.

We find that, compared with studies that have looked at horizontal mismatch (mismatch between the type of education demanded and supplied within a specific education level) or inter-curricular mismatch (the specific skills learned in a specific educational program and the demanded from graduates by employers), the attention paid to vertical mismatch or overeducation has been quite substantial. Reading through reviews on overeducation and underemployment one can concur with the point made by Scurry & Blenkinsopp (2011) that "… preoccupation with measurement of underemployment has stymied the development of research that might help in understanding the dynamics of the unfolding experience of graduate underemployment." Sloane (2003) states that the main contribution of the overeducation literature has been to highlight that it matters where a worker is employed.

In this chapter we have analyzed to what extent the literature on overeducation and underemployment contributes to evidence based education. A necessary condition for a contribution to evidence based education is that reviews on this topic should be systematic reviews. This implies that the reviews contain an explanation and description of the search strategy and the inclusion and exclusion criteria used to select papers for review. We found that very few of the

review studies on overeducation and underemployment are systematic reviews. In the large majority of the review studies the search strategy is not described at all, it remains unclear on what criteria studies have been selected for inclusion in the review and also basic information about the studies included are not presented. Also a critical appraisal of the studies and their findings is often lacking. Most reviews take the claims made in the studies reviewed at face value. Very few reviews raise issues like the causality in the relation between overeducation and its returns and about the validity and generalizability of the findings. From this we conclude that the usefulness and relevance of these review studies for evidence based education is limited to say the least. Even after forty years of research the evidence base on overeducation and underemployment in the labor market remains slim.

The overeducation literature can be criticized for its rather static nature. Any worker with more education than required for the job is considered overeducation. This ignores that overeducation may be conditioned by experience, tenure on the job and on-the-job training. A middle aged worker with a university degree who works for ten years as a management support staff may be overeducated, whereas a recent college graduate whose first job is in management support may not be really classified as overeducated.

How useful is the overeducation and underemployment literature for evidence based education? The answer to this question must be: its usefulness is limited. The first caveat is that the returns to overeducation – which may indicate the welfare losses of mismatch – may be biased and do not reflect causal effects. Secondly, there is evidence to assume that for many workers overeducation and underemployment are temporary phenomena and not a permanent state. Many overeducated or unemployed workers find more fitting jobs over time. Thirdly, there is evidence to assume that overeducation – at least partly – compensates for a lack of other productive skills. Some of these other skills are accumulated over time – f.e. experience – thereby reducing overeducation. All of these arguments limit the need and potential for policy interventions. Finally, and from an evidence based perspective rather important, the very few of the reviews on this topic are systematic reviews. Most of the reviews seem to be based on a rather selective reading of the literature. Almost never authors of the reviews make clear how the search for the literature has been conducted. At some points one gets the impression that authors have searched for the literature that supports their ideas about the incidence and effects of overeducation and underemployment, rather than that they let the findings speak for themselves.

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Matching of Human Capital to Jobs in Time of Crisis: An Analysis of Employers' Strategies in the Netherlands

Florian Tomini en Sofie Cabus

Abstract

The tightening labor market conditions all around the World are constraining employers to invest more on human capital formation for their employees as well as look for more effective human resources tools. The financial crisis and its aftermath created yet a more stressing and challenging environment, with increasing demands to be competitive in the market, which in turn meant greater efforts in maintaining a good match between skills of the staff and the jobs offered. Many public and private companies had to adopt with the new changing environment by shutting down expensive and ineffective operations and by finding innovative ways to increase productivity. Most of the skills matching problems that employers faced before, during and after the financial crisis related to the difficulties in the recruitment of new staff, the retention of staff, staff not sufficiently qualified, staff not available, or low productivity of personnel. Despite the fact that there exist a body of evidence on how employers choose to overcome such bottlenecks, our knowledge on their best strategies to overcome such situations remains limited. Moreover, while governments struggled to ameliorate the employment situation on the labor market little is known about the relation between their undertaken policies and the matching of human capital to companies. This paper investigates the attitudes of employers on the strategies for resolving different bottlenecks in terms of matching of human capital to the jobs in public and private companies before and after the financial crisis as well as sheds light on the links between the government policies aiming to ameliorate the employment situation on the labor market and a set of outcome variables that relate to matching human capital to companies. We use data from the Arbeidsvraagpanel 2011-2012 to identify bottlenecks in terms of human resources as well as education-labor market mismatch. We employ a multinomial logit to model the bottlenecks (before and after the financial crisis) as well as quintile regressions for modeling the mismatch in human capital. We find that it is unlikely for companies that have not had any past staff-related bottlenecks to point out to any of the strategies in order to deal with future bottlenecks. Among companies that had staff-related bottlenecks in the past education was seen as a strategy to deal with qualification of staff, increased public investment in ICT was related to staff recruitment and retention, hiring foreign labour force as a solution to qualifications, low

productivity, retention and recruitment, decreasing the wage rate growth was related to lack of productivity, and availability of publicly funded child care was seen as a solution for retention of staff. On the other hand, policies like availability of publicly funded child care and employer less responsible for absenteeism were also related to lower degrees of mismatch of the human capital. Our results show that certain policies are related to lower mismatch and also viewed as effective policies by the employers, especially giving the conditions faced immediately after the financial crisis. Yet, more investigation is needed in order to conclude on the effectiveness of such measures.

Keywords: Bottlenecks; Human Capital; Human Resources; Mismatch policy measures;

Paper not yet available

Work or Schooling? On the Return to gaining in-School Work Experiences

Sofie Cabus en Carla Haelermans

Abstract

Wages are a composite measure of the return to education and the return to work experiences. Work experiences are often defined as workers who gain experiences on-the-job. However, work experiences can also be part of a study curriculum in vocational secondary education. We estimate the return to in-school work experiences by comparing the Heckman (1979) selection model and the Rubin (1974, 2006) matching model. First, we show that students with in-school work experiences earn +16 percent more in the first years of labour than their theoretical peers. Second, we indicate that both empirical models do not appropriately deal with censored observations in the presence of an informal market. Including information on a set of censored observations increases the effect to +22 percent.

Keywords: Human Capital; Return to Education; Selection; Work Experience; Vocational Education;

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1. Introduction

The literature indicates that students with vocational specialization are inclined to leave education at an earlier point in their school career than their theoretical peers (Ryan, 2001; Staff and Mortimer, 2008). Vocational youth leave education earlier, or even drop-out of school without secondary school-leaving certificate, for two comprehensive reasons. First, youngsters enrolled in low end vocational- and pre-vocational education or training (VET[1]) more often have problems, such as growing up in disadvantaged neighborhoods; health issues; juvenile delinquency; wrong study choice; unauthorized school absenteeism; or bad relationship with peers, at home and at school (Rumberger, 2011; De Witte et al., 2013).. Second, students with vocational specialization can also trade-in school for a job, irrespectively of their problems, and do so at an earlier point in their school career than their theoretical peers due to the opportunity costs of schooling. This paper especially focuses on the latter by exploring the differences in wages between school-leaving work-oriented and theoretical students. Traditional human capital theory defines the opportunity cost of schooling as the monetary return of paid labour (Mincer, 1958; Becker, 1962, 1964). Mincer (1958) argues that wages are a composite measure of the return to education and the return to work experiences. He defines work experiences as workers who gain job market experiences. However, work experiences can also be gained by students in VET, for instance, by work placement, internships or dual tracks. Compared to gaining work experiences on-the-job, the school institution keeps playing an important role in educating students. Therefore, we refer to this concept as gaining 'in-school work experiences'. The hypothesis is that, if work-oriented students earn higher wages than theoretical students owing to work experiences, then work-oriented students have higher opportunity costs of staying in school. This could then explain why they make the school-to-work transition at an earlier point in the school career than their theoretical peers. We test this aforementioned hypothesis by estimating the differences in wages between school-leaving work-oriented and theoretical students particularly owing to in-school work experiences.

The contributions of this paper to the previous literature are threefold. First, there is a lively debate in the literature on the return to gaining work experiences. Several authors provide evidence on the positive relationship between students' work experiences and labour market wages (e.g. Ruhm, 1995; Hotz et al., 1998; and Light, 2001; Staff and Mortimer, 2008). Staff and Mortimer (2008), for example, show that extensive work experience at an early point in the school career is less beneficial than a prolonged educational investment, especially for people from ethnic minorities and low socioeconomic background. However, almost all these studies define work experiences as working beyond compulsory school-time. Gaining practical experiences could also be part of an occupational

school curriculum, where students gain practical experiences during their compulsory school-time as part of the study load. It is in this respect that literature and research on the return to in-school work experiences is scarce. One example is provided by Hanushek et al. (2011). The authors have compared general- to vocational education and the distinct impact on labour market outcomes in the long-run. They use data on several European countries and compare the labour market outcomes of school-leaving youth with different educational backgrounds and abilities in a difference-in-differences framework. Matching estimation is used to foster comparability of student populations across countries. Hanushek et al. (2011) conclude that individuals with a background in vocational education, in first instance, have better employment outcomes than individuals with a background in general education. However, in the long-run, this is completely the opposite. Another recent example is provided by Black et al. (2012). The authors recently studied the effect of in-school training programs in Australia. Similar as in Hanushek et al. (2011), Black et al. (2012) used propensity score matching estimation techniques for aiming at a causal evaluation of the program. They argue that these programs have decreased the likelihood of dropping out of school and, moreover, increased chances of finding work. These results were mainly driven by in-school training programs that also included a structured workplace learning component. The topic of this paper is more comparable with Hanushek et al. (2011) and Black et al. (2012) than with the other previously discussed literature, as our paper also employs propensity score matching techniques to obtain meaningful comparisons between a 'treatment group' (i.e. those students who gain in-school work experiences), and a 'control group', (i.e. those students who do not). Additionally, Black et al. (2012) used previous tests taken by the students in order to control for, otherwise unobserved, ability. Ability matching accounts for endogeneity issues, potential selection effects and differences in student-level and household-level characteristics. This paper also includes measured ability tests scores, and, additionally, adds to the previous literature by using another, potentially better control group, namely: theoretical vocational students instead of non-vocational students. The previous literature used students enrolled in non-vocational (general) education in order to construct an appropriate counterfactual outcome. We compare the return to education for two very similar groups of students of the same cohort that follow either a theoretical-oriented track or a work-oriented track in VET. Thus, we have the possibility to focus on VET-students only. This is the first contribution to the literature.

Second, the analysis is performed using rich data from the Netherlands. The Netherlands is an interesting case study with regard to the return to gaining in-school work experiences. Since the early 1900s, the Netherlands is offering in-school work experiences to school-age students. Among the EU

Member States, the country has one of the oldest histories in vocational school curricula (Onstenk and Blokhuis, 2007).

Owing to the Dutch data, we are able to deal with several empirical issues as pointed out in the previous literature (e.g. Oosterbeek and Webbink, 2007). One of those concerns is the potential bias that could arise from selectivity in educational decisions and labour market decisions (i.e. Griliches, 1977; Heckman 1979). Hotz et al. (1998) add to this that the influence of, often unobserved, innate ability and socioeconomic background of the household are important drivers of omitted variable bias. This has been confirmed in the recent work of Müller and Wolter (2011). The authors discuss that unobserved heterogeneity in the students' background and innate ability is directly hampering statistical inference with respect to the determinants of educational- and labour market outcomes. To meet these critiques, we use a well-considered approximate of students' innate ability (i.e. student test scores on the Dutch standardized exam that every student performs before placement in an educational track at the start of secondary education, CITO exam scores), and student-level and household-level characteristics, as instruments in an education-labour market regression (Black and Smith, 2004; Tobias, 2003). Hereby, we use propensity score matching estimation techniques that allow us to account for the likelihood that a student will gain in-school work experiences based on his/her innate ability and socioeconomic background.

We use longitudinal data on a cohort of students enrolled in vocational tracks in secondary education in the Netherlands in 2000 (Kuyper et al., 2003; Batenburg et al., 2007; Zijsling et al. 2007). Monitoring the performance of students enrolled in VET is important and of interest, because it has the largest share of students in secondary education, and because of large financial investments owing to the (partly) practical nature of VET courses (e.g. Weltz, 2005). In the Netherlands, students enrolled in VET can choose between a theoretical- and a work-oriented track. Because of the system of early ability tracking in the Netherlands, the data also contain standardized student test scores on math and language, as well as student-level, household-level and school-level characteristics, and labour market experiences. Of special interest for our analysis are the student test scores on the standardized CITO exams, as these exams are especially designed to measure the students' innate ability at the start of secondary education and have a high level of precision. We evaluate the labour market outcomes of students in the work-oriented tracks and compare these outcomes with those of students with a theoretical vocational background. As such, contrary to the study of Hanushek et al. (2011), we only compare students enrolled in VET with each other, making the counterfactual outcome in a quasi-experimental set-up feasible. Thus, as a major advantage, our approach fosters to find individuals with great overlap in innate ability and socioeconomic background. This is an important feature for an experimental set-up in which we use propensity score matching techniques.

Third, empirically, we compare the estimates from two different methods, namely: the Heckman (1979) selection model and the Rubin (1974, 2006) matching model. Although both methods are conceptually distinct, this paper shows that they should yield similar estimates when appropriately dealing with comparable treatment and control group students. To our best knowledge, the previous literature did not provide such meaningful comparison between the estimates of these methods. It also allows us the opportunity to have a discussion on censored observations and missing data in a labour market analysis. In particular, our data include information on individuals who are not officially in paid labour, but who still earn an income (e.g. owing to unemployment allowances, social security benefits, or working in the parents' company). We check for the robustness of the main results by including this information into the regression.

This paper proceeds as follows. In Section 2 we shortly describe the theoretical framework that this paper is based on. Next, in Section **'**Identification strategy' we explain the intuition of the identification strategy used for estimating the return to gaining in-school work experiences. Section 4 describes the data and descriptive statistics. The results are presented in Section 5. Section 0 concludes.

2. Theoretical framework

To estimate the return to gaining in-school work experiences, we build on the traditional human capital theory and the return to education, as developed by Mincer (1958, 1972) and Becker (1962, 1964), among others. As follows, we start from Mincer's earnings function, and, then, isolate experiences from the wage composite measure. Mincer's earnings function (Mincer, 1974) predicts that wage (W) is dependent on the number of years of schooling (S), the number of years of in-school work experience (E_S), the number of years of tenure (i.e. after-school work experience); the squared term of years of experience $(\mathrm{E}_W + \mathrm{E}_S)^2$ and other individual or environmental variables (X). We then may write:

$$\log(\mathrm{W}) = \mathrm{aS} + \mathrm{b}(\mathrm{E}_S + \mathrm{E}_W) + \mathrm{c}(\mathrm{E}_S + \mathrm{E}_W)^2 + X'd\ , \qquad (1)$$

where a denotes the return to schooling, and b and c the return to work experience.

In order to estimate the return to gaining in-school work experiences, we wish to isolate the effect of E_S from the wage composite effect. Therefore, we consider the case in which experience can be part of the regular (i.e. compulsory) schooling curriculum. Students either choose a practically oriented

track or a theoretically oriented track in secondary vocational education. The practically oriented track partly consists of learning on-the-job, which implies that schooling takes place while gaining experience on the job. The total single years of schooling are similar for all individuals in both options, so that we can cancel out this term from equation (1). Note that we acknowledge that age differences between students in the same class can occur owing to e.g. date of birth or retention in grade. This may lead to differences in the total years of schooling, too. We explicitly deal with this by matching treated and untreated students on age, and including age as a covariate. It is further acknowledged that the variable E, in fact, can be split into two parts: experience E_S and tenure E_W (Dustmann and Pereira, 2008). This paper only focuses on the return to in-school work experiences E_S. However, theoretically it can be the case that, for practical students, in-school work substitutes after-school work, while theoretical students do a sideline after-school. If, this would be true, than our assumption of comparability of the treated (practical) and untreated (theoretical) would be violated because of differences in tenure. It is then important to argue that tenure can be dealt with as negligible, as is the case in this paper, so that it cancels out from equation (1). First, we only look at wage differences one year after graduation from vocational secondary education. Second, and most importantly, the Dutch law on gaining (after-school) work experiences for legal pay before the age of 16 is strictly regulated. It indicates that youngsters can be in the labor force earliest between 15-25 years (see also Statistics Netherlands, cbs.nl, 2015). Therefore, we consider tenure owing to gaining after-school work experiences as negligible. Furthermore, in-school work experiences are not paid, or only with respect to allowance for expenses. Gaining these work experiences through work placement, internships or dual tracks is considered part of the school curricula. Thus, one may conclude that E_W drops from equation (1).

As such, we wish to compare individuals who gained in-school work experiences, with individuals who followed the theoretical track and did not gain experience on the job. This implies that having experience or not can be modeled as a dummy variable ($\mathrm{E}_S \in \{0,1\}$), so that including the quadratic term in Mincer's earning equation becomes redundant.

In order to isolate E_S from X, we propose to match practical oriented students to theoretical oriented students based on a rich set of observed characteristics. If, individuals with in-school work experiences are, on average, comparable with individuals having no work experiences, then this should cancel out X from equation (1). We then may rewrite equation (1) as a simplified Mincer's earnings function with, for example, W_C the average wage of individuals in the control group, and W_T the average wage of individuals in the treatment group:

$$\log(\mathrm{W_T}) - \log(\mathrm{W_C}) = \mathrm{bE}_S \,. \qquad (2)$$

The estimate b denotes the returns to gaining in-school work experiences and, in fact, captures the differences in wages between practical and theoretical oriented students. Since in-school work experiences is expressed as a binary variable in the paper, it is acknowledged that these wage differentials should be interpreted as the returns to secondary vocational education with in-school work experience rather than returns to in-school work experience.

Over the years, several critical remarks have been posted on Mincer's earnings equations, some of which are relevant for our paper, but most of which are not. Lemieux (2006), for example, criticized the fact that: (1) experience is only included as a singular and quadratic term, instead of also as quartic term; (2) that schooling is not included as a quadratic term; and (3) that cohort effects cannot be included. We meet these comments by modeling experience as a dummy variable, using only one cohort of individuals, and, hereby, modeling schooling as equal for all individuals.

Heckman et al. (2003) further argue that Mincer fails to take into account tuition fees, taxes, nonlinearity in schooling, non-separability between experience and schooling and uncertainty of future earnings. In spite of these critiques, we are able to deal with these issues with care. First, as there are no tuition fees in the Netherlands for secondary education, this argument is not relevant in our case. Second, our data reports wages after taxes. Third, since schooling is similar for everyone, the nonlinearity in schooling does not pose a problem. Fourth, we manage to isolate the experience effect from the wage composite effects, so that non-separabilty of experience and schooling should not pose a problem as well. And to conclude, we only focus on the short run in this paper, which makes the long run uncertainty of future earnings irrelevant.

3. Identification strategy

3.1. Econometric challenges

Three related weaknesses with respect to the estimation of the return to schooling have been argued by, among others, Hoxby (1997), Heckman and Vytlacil (2001), and Black and Smith (2002). The first weakness deals with "[...] the failure of the "common support" condition (Black and Smith, 2002, p.100)." We argue that we do not violate the condition of common support in our paper, mainly because we use the beneficial features of the early ability tracking system in the Netherlands. This system implies that similar students, or in other words, students who have similar test scores on the standardized exam at the end of primary education, are assigned to similar tracks in secondary

education. As such, students at the start of secondary education follow an educational track that `fits best' their ability. Consequently, students in vocational tracks are very likely to have similar covariate distributions, when it comes to `the marginal student'. The marginal student in this respect is a student who had a test score just below (above) the test score that would allow him/her to follow a higher (lower) educational track.

Tobias (2003), among others, points to the second potential weakness in estimating the return to schooling, which is the assumption of linearity of ability. In line with Black and Smith (2002), we use a propensity score matching framework, in which we match on the estimated likelihood of being enrolled in work-oriented vocational tracks based on the set of covariates X, rather than including X directly into the regression. The likelihood of being enrolled in work-oriented vocational tracks will then be a function of X, which can be estimated by a flexible parametric discrete choice model (e.g. a Probit model). As such, we include the test scores of students on the standardized CITO exams in X, so that the likelihood of gaining in-school work experiences is also a function of ability (therefore, we often refer to this approach as "ability matching").

A third potential weakness deals with the problem of selection into paid labour. This weakness is also discussed in the next section as the problem of censored observations, as we often do not observe wages of those individuals who are not in paid labour. Therefore, we discuss in-depth an empirical strategy largely based on Heckman (1979) and Rubin (1974, 2006).

3.2. Selection into paid labor

In this section, we discuss how we can deal with self-selection in the labour market, or the problem of censored observations, from three different angles: (1) Heckman selection model; (2) matched selection; and (3) elabourated selection, given that we have knowledge on the labour force status of the individuals not in formal paid labour.

Heckman (1979) argues that selectivity is inevitable when it comes to observational studies. The OLS estimate is then biased and inconsistent and statistical inference is hampered. Studies with labour market outcomes are rather easy examples in showing where the problem of selectivity arises: if one is not in the labour market, we do not observe his/her job market wage. The previous literature has shown that the group of individuals not in paid labour is associated with several background characteristics (e.g. gender, ethnicity, health status, or grade point averages, educational field or level). Thus, being in paid labour is seldom a random process.

Heckman (1979) shows in his work that, if wages are observed as a result of being in paid labour, the market wage is greater than the reservation wage. The reservation wage is the minimum job market

wage an individual is satisfied with in order to be willing to work. Denote the individuals' wages of those not in the labour market as the latent variable (y^*). If the market wage is less then the reservation wage ($y < y^*$), we do not observe the wage, as the individual is not willing to work, and, thus, not in paid labour. We can formalize Heckmans' selection model in two equations. The first equation is called the selection equation, and may be written as (Guo and Fraser, 2010):

$$\mathrm{pl}_i = \alpha_0 + \sum_{k=1}^{K} \delta_k X_{ki} + \varepsilon_i \,, \qquad (3)$$

where $\mathrm{pl}_i \in \{0,1\}$ denotes the paid labour status of an individual i with (0=not in paid labour) and (1=in paid labour); α_0 a constant; X_{ki} a vector of exogenous student-level and household-level characteristics; and ε_i the error term. In fact, we estimate the probability of being in paid labour in equation (3) conditional on a set of characteristics that is considered sufficiently informative with respect to the self-selection in paid labour.

One can now easily see that wages are observed if:

$$\alpha_0 + \sum_{k=1}^{K} \delta_k X_{ki} + \varepsilon_i > 0 \,. \qquad (4)$$

The next equation grasps the treatment effect:

$$\mathrm{y}_i = \alpha_1 + \theta \tilde{T}_i + \lambda \widehat{\mathrm{pl}}_i + u_i \,, \qquad (5)$$

where λ controls for selectivity in the treatment equation; $\widehat{\mathrm{pl}}_i$ is the conditional probability that an individual is in paid labour as estimated in equation (3); $\tilde{T}_i$ an indicator of the treatment status after matching with (T=0) the matched untreated individuals, and (T=1) the treated individuals; and u_i a residual. The estimate of interest is θ, the average treatment effect of the treated (ATT) or, in other words, the return to gaining in-school work experiences.

We can argue from equation (5) that Heckman selection model is actually similar to 'matched selection' or 'ability matching', when we construct an appropriate counterfactual outcome in T (see also Guo and Fraser, 2010). This would imply that the level of the reservation wage in both control and treatment groups are, on average, the same, so that selectivity is not an issue. Heckmans' selection model dealing with censored observations is then unnecessary if and only if the treated and matched untreated groups are equal in X. Researchers also debated the exclusion restriction for a Heckman selection Model. In fact, it is indicated that an exclusion restriction is unnecessary in a non-linear bivariate normal selection model (e.g. Millimet and Tchernis, 2012), as identification then relies on functional form assumptions. Furthermore, we combine an approach in which results from the Heckman selection model are compared with estimates from using the non-parametric Kernel

matching estimator (see Section 5). We consider this a good sensitivity analysis, because those problems arising from linearity are solved by using the latter estimator. Note that we discuss the results of the different estimators in Section 5. We then may rewrite equation (5) as:

$$\mathrm{Y}_i = \alpha_1 + \theta\tilde{T}_i + u_i \text{ , observed only if } \mathrm{pl}_i = 1 \,. \qquad (6)$$

The third angle is that we also include information on individuals who report income owing to unemployment or social security benefits, or other sources that generate (a modest) income (such as volunteer work or working for your parents 'company). We call this model `elaborated selection', as individuals cannot only select into formal paid labour, but also into other activities, which result in an income. This approach can only be feasible if the data is sufficiently informative with respect to those individuals not in formal paid labour (see Section 5). After applying matching, we estimate the following parametric estimate for the return to gaining in-school work experiences:

$$\mathrm{Y}_i = \alpha_1 + \beta\tilde{T}_i + \sum_{j=1}^{J}\gamma_j \text{labour force status}_{ji} + \theta(\tilde{T}_i * \mathrm{pl}_i) + u_i \,, \qquad (7)$$

where $\text{labour force status}_{ji}$ denotes a vector with the individuals' labour force status $\mathrm{j} \in \{1,2,\ldots,\mathrm{J}\}$. In order to estimate the parameter θ, we first compute an interaction effect between the treatment status and paid labour status. The ATT can then be interpreted as conditional on the treatment and the labour force status. Controlling for labour force status in equation (7) is necessary, as we wish to take into account that, for example, students can also combine learning and working and, consequently, devote less time to being in paid work. Note that equation (7) can be extended with a vector X_{ki} of student-level and/or household-level control variables.

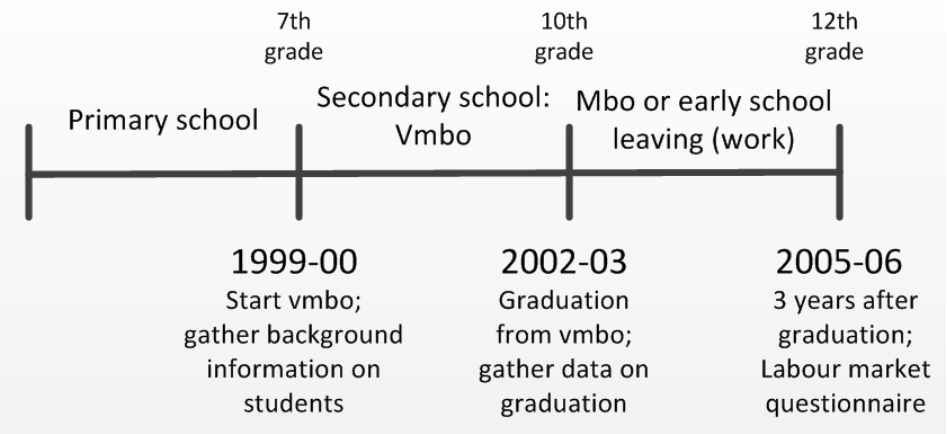
4. Data and descriptive statistics

We use panel data of a cohort of Dutch students entering secondary education in the school year 1999-00 (VOCL'99, Voortgezet Onderwijs Cohort Leerlingen) (Kuyper et al., 2003; Batenburg et al., 2007; Zijsling et al. 2007). The sample students are followed up at three different moments in time up till the year 2005-06. Figure 1 shows the timeline of this cohort. In 1999-00, the students in our data enter vmbo, the lowest of the three secondary education levels, based on the CITO exam and a recommendation given in elementary school (i.e., ability tracking). Note that in the Netherlands almost 50 percent of the students enroll in vmbo. In vmbo, 4 tracks in total exist, two are work-oriented, and two are theoretical-oriented, and most schools offer all four tracks, taught by the same teacher force. These tracks differ in *where* the student learns, but are similar in other characteristics. In the work-oriented tracks, students learn on the job, whereas in the theoretical tracks students learn in the classroom. The amount of schooling is the same for all tracks. However, in learning on

the job, practical students simultaneously gain work experiences, although it cannot be quantified how much, given the learning nature of their position in the company.

Also, if one obtains a vmbo certificate after 4 years, it is not considered a 'valid' secondary school-leaving certificate. As such, vocational students should enroll in post-secondary vocational education (mbo; 4 years) in order to obtain a school-leaving certificate valid for labour market entrance. Nonetheless, it is observed that early school-leaving in the years after finishing vmbo is substantial (23.3 percent) in both theoretical and practical tracks, and, additionally, that most students in mbo combine work with learning also leading to substantial dropout rates (8.9 percent) (Statistics Netherlands, statline.cbs.nl, year 2006). Therefore, wages are observed for most vmbo graduates. In our data, we observe that 89.4 percent of vmbo school-leaving youth are reporting a wage.

Figure 1: Timeline for used data cohort



In the final year of the longitudinal study 2005-06, the sample students filled out a questionnaire asking about their educational and labour market outcomes and further aspirations. Note that these students should either still be in mbo, or have dropped out. Also note that many students in mbo participate in a track that involves working for 4 days and going to school for the fifth day each week. The VOCL'99 data consist of 19,384 individuals of whom 4,048 observations (N) have had an occupational school curriculum. The data on these vocational students are combining administrative and survey information from students and their parents at three different moments in time. These students entered secondary education in 1999-00, should have graduated from vocational secondary education (vmbo) in 2002-03 and are being followed until 2005-06, where they either have entered the labour market or are attending continued vocational education, or are unemployed, receiving social benefits or something alike. We call this their current labour force status.

From the total sample of 4,048 individuals, only about 50% (N=2,047) of observations are used in the analysis due to missing values on the matching variables CITO scores on mathematics or language

(1,374). Also, some students follow a combined track of practical and theoretical education (about 8%), and another small share of students (less than 1%) receive supported education during their secondary school curriculum (lwoo). Students with support education have a special administrative status, so that it is unclear for the researcher whether these students follow a practical, theoretical or combined track. We remove these observations from the total sample. In total 48.1% (N=984) of students attend a theoretical occupational school curriculum and 51.9% (N=1,063) a work-oriented vocational track.

We acknowledge that attrition in our data is substantial. Although the data are most likely not nationally representative (anymore) as a result of attrition, we deal with missing data by using matching analysis. Matching analysis controls for the probability that an individual enrolls in a practical track based on observed individual characteristics. As such, if one believes that the confounding assumption is met by matching analysis, then missing data should not be of an issue as a comparison between control and treatment group cancels out attrition (for an in-depth discussion, see also Rosenbaum and Rubin, 1984; D'Agostino and Rubin, 2000). We provide evidence of the confounding assumption in Section 5.

Table 1: Descriptive statistics of the matching variables (1999-00, N=2,047)

Variable	Mean	Std. Dev.	Min	Max
Treatment Indicator	0.52	0.5	0	1
Cito score (period1)				
CScore Math	10.47	3.93	1	20
CScore Language	11.12	3.31	1	20
Gender	0.43	0.49	0	1
Country of origin				
Netherlands	0.92	0.26	0	1
Morocco	0.01	0.09	0	1
Sur/Ant/Aruba	0.01	0.09	0	1
Turkey	0.01	0.08	0	1
Other	0.05	0.22	0	1
Age of child (period1)	12.55	0.58	12	14
Religion/Ideology				
None	0.26	0.44	0	1
Catholic	0.35	0.48	0	1
Protestant	0.13	0.34	0	1
Reformation	0.12	0.33	0	1
Islam	0.02	0.13	0	1
Other	0.12	0.32	0	1
Socioeconomic status				
socioecon1	0.09	0.28	0	1
socioecon2	0.17	0.38	0	1

socioecon3	0.54	0.5	0	1
socioecon4	0.16	0.37	0	1
socioecon5	0.04	0.19	0	1
socioecon6	0	0.07	0	1
Marital status				
Married	0.91	0.29	0	1
Living together	0.03	0.16	0	1
Never married	0.01	0.07	0	1
Widow	0.01	0.11	0	1
Divorced	0.05	0.21	0	1
Children in family	2.59	1.11	1	5
Culture parent1-child[(3)]	0.01	0.11	0	1
Culture parent2-child[(3)]	0.02	0.13	0	1
Hourly wage	4.93	3.32	0.01	56.37
Still in school	0.01	0.13	0	1
Labor-force-status: Paid labour	0.57	0.5	0	1
Labor-force-status: Getting social benefits	0.01	0.08	0	1
Labor-force-status: Registered at unemployment organization	0.01	0.11	0	1
Labor-force-status: Registered at employment agency	0.07	0.25	0	1
Labor-force-status: Working at company parents	0.03	0.16	0	1
Labor-force-status: Does housekeeping	0.19	0.39	0	1
Labor-force-status: Volunteer work	0.1	0.31	0	1
Labor-force-status: Long illness	0.01	0.09	0	1

Note: CITO test scores are at the start of secondary education. 'Culture parent1(2)-child' denotes potential cultural differences between the parent(s) and the child.Socion1-Socion6 denotes socioeconomic status ranging from lowest (Socion1) to highest (Socion6).

Table 1 presents the descriptive statistics of the student and school characteristics in 1999-00 and of the outcome variable and labour force status in 2005-06. We observe that students have, on average, 10/20 with respect to CITO math, and 11/20 with respect to CITO language. About 40 percent of the students are male, and the students from our sample are, on average, 12.5 year-olds in 1999-00. Furthermore, Table 1 shows their country of origin, their religion, their socioeconomic status, and their parents' marital status. Socioeconomic status group 1 implies the highest socioeconomic status, whereas group 6 has the lowest status. This measure is approximated by the highest level of education of the parents (Zijsling and van der Werf, 2007). The table also provides information on cultural differences between the parents and the child (see variables `culture parent1-child' and `culture parent2-child'). These variables indicate cultural differences between first and second, or second and third generation immigrants by looking at the language and cultural community as indicated by the parents compared to the children. Information on number of children in the family is also included in Table 1.

With respect to the wage information in 2005-06, Table 1 shows that the average hourly wage is almost 5 euro per hour. The majority of students that earn an income have reported that they are

officially in paid labour (57%), about 10 percent is doing volunteer work, a small share still in school (2%), or is unemployed (less than 10% in total). About 19 percent does the housekeeping.

Table 2: Independent two-tailed T-test of the confounding variables of treated and untreated students

	control group (N=984)		treatment group (N=1063)		t-stat
Variable	Mean	Std. Dev.	Mean	Std. Dev.	
Cito score (period1)					
CScore Math	11.941	3.599	9.111	3.728	17.447
CScore Language	12.232	2.969	10.093	3.281	15.422
Gender	0.414	0.493	0.436	0.496	-1.003
Country of origin					
Netherlands	0.919	0.273	0.929	0.256	-0.918
Morocco	0.005	0.071	0.012	0.11	-1.731
Sur/Ant/Aruba	0.012	0.11	0.003	0.053	2.487
Turkey	0.004	0.064	0.008	0.092	-1.252
Other	0.06	0.238	0.047	0.212	1.301
Age of child (period1)	12.458	0.549	12.634	0.602	-6.884
Religion/Ideology					
None	0.286	0.452	0.235	0.424	2.602
Catholic	0.368	0.482	0.331	0.471	1.743
Protestant	0.125	0.331	0.143	0.35	-1.192
Reformation	0.114	0.318	0.131	0.337	-1.167
Islam	0.011	0.105	0.023	0.149	-1.989
Other	0.097	0.295	0.137	0.344	-2.866
Socioeconomic status					
socioecon1	0.056	0.23	0.114	0.318	-4.694
socioecon2	0.137	0.344	0.208	0.406	-4.233
socioecon3	0.537	0.499	0.542	0.498	-0.239
socioecon4	0.214	0.411	0.109	0.312	6.562
socioecon5	0.05	0.218	0.024	0.155	3.054
socioecon6	0.006	0.078	0.003	0.053	1.119
Marital status					
Married	0.92	0.272	0.9	0.3	1.532
Living together	0.024	0.154	0.027	0.163	-0.411
Never married	0.003	0.055	0.008	0.086	-1.384
Widow	0.011	0.105	0.011	0.106	-0.024
Divorced	0.042	0.2	0.054	0.225	-1.266
Children in family	2.508	1.001	2.661	1.196	-3.13
Culture parent1-child	0.015	0.123	0.011	0.106	0.783
Culture parent2-child	0.015	0.123	0.017	0.129	-0.303

Note: See note from Table 1

Table 12: Independent two-tailed T-test of the outcome variables of treated and untreated students

	control group (N=984)		treatment group (N=1063)		t-stat
Variable	Mean	Std. Dev.	Mean	Std. Dev.	
Hourly wage	4.75	3.431	5.097	3.215	-2.3595
Log hourly wage	1.274	1.01	1.348	1.058	-1.6171

As follows, we perform a standard check of the comparability of the treatment group (N=1063) and control group (N=984), before matching them. Table 2 and Table 3 present the T-test statistics on the background characteristics and on wages, respectively. From Table 2, we conclude that there are significant differences between treated and untreated students with respect to CITO test scores and several background characteristics. And from Table 3, we observe that treated students earn, on average, about 5 euros and 10 cents per hour, that is about 35 cents more than untreated students.

5. Results

5.1. Matching results

We use the Kernel matching estimator in order to estimate the likelihood to be in a practical track in vocational secondary education based on observed characteristics. We match based on CITO exam scores, gender, ethnicity, age, religion, socioeconomic status, parents' marital status, number of children in the family and the culture of the parents.

Kernel matching reduces the curse of dimensionality owing to its non-parametric approach (Rosenbaum and Rubin, 1983). The Kernel matching estimator uses propensity score matching in order to estimate the extent to which treated and untreated individuals have overlapping background characteristics. A standard discrete choice Probit model is used for the estimation of the propensity score values. A specific feature of the Kernel matching estimator is that it assigns (nonzero) weights to matched untreated individuals in order to make these individuals comparable with the treated individuals. These weights are based on comparing all individuals, within a well-specified subgroup of individuals, with each other at the same time. These subgroups are defined by a chosen bandwidth that divides the Kernel density function. We estimate equation (6) (Section 'Identification strategy') using the default bandwidth by Epanechnikov approximation. We choose Epanechnikov approximation over the alternative, the normal (Gaussian) approximation, because the normal approximation has no restriction on the common support (Silverman, 1986; Black and Smith, 2002). The bandwidth by Epanechnikov approximation trims away individuals at the tails of the

distribution, as such stricter dealing with the problem of common support (Haedler and Marron, 1985).

Table 4 presents the descriptive statistics of the Probit regression. These estimates indicate, for instance, that students who perform badly on their CITO exam are more likely to be in a practical track. The same holds for students with a lower socioeconomic status.

Table 4: Probit regression of background characteristics on the chance of being in the practical track

Variable	Coef.	Std. Err.	Variable	Coef.	Std. Err.
Performance on math	-0.106	0.009	Socioeconomic status		
Performance on language	-0.088	0.011	socioecon1	-0.052	0.135
Gender(Male=1)	0.146	0.065	socioecon2	-0.309	0.122
Age	-0.140	0.688	socioecon3	-0.802	0.139
Country of origin(Netherlands=1)			socioecon4	-0.808	0.197
Morocco	-1.035	0.429	socioecon5	-0.792	0.481
Sur/Ant/Aruba	-0.185	0.676	Family(Married=1)		
Turkey	-0.237	0.142	Living together	0.303	0.190
Other	0.245	0.053	Never married	0.715	0.450
Religion/Ideology(None=1)			Widow(er)	0.143	0.286
Catholic	0.114	0.080	Divorced	0.264	0.147
Protestant	0.191	0.105	Total children	0.109	0.030
Reform.	0.200	0.111	Cultural background		
Islam	0.099	0.596	Culture parent(different=1)	-0.601	0.394
Other	0.429	0.113	Culture partner(different=1)	0.512	0.350
			constant	-1.071	0.700
Number of obs=2,047					
LR chi2(25)=516.340					
Prob > chi2=0.000					
Pseudo R2=0.182					

Note: See note from Table 1

Table 5: Independent two-tailed T-test of the confounding variables after matching

	control group (N=981)		treatment group (N=1054)		t-stat
Variable	Mean	Std. Dev.	Mean	Std. Dev.	
Cito score (period1)					
CScore Math	9.273	3.707	9.16	3.703	-0.38
CScore Language	10.441	2.871	10.143	3.248	-1.46
Gender	0.475	0.5	0.434	0.496	-1.16
Country of origin					
Netherlands	0.938	0.241	0.929	0.257	-0.71
Morocco	0.008	0.088	0.012	0.11	0.94
Sur/Ant/Aruba	0.003	0.051	0.003	0.053	0.14
Turkey	0.008	0.089	0.009	0.092	0.1
Other	0.044	0.204	0.047	0.213	0.36
Age of child (period1)	12.57	0.575	12.626	0.597	1.42
Religion/Ideology					
None	0.245	0.43	0.235	0.424	-0.32
Catholic	0.323	0.468	0.331	0.471	0.29
Protestant	0.148	0.355	0.144	0.351	-0.12
Reformation	0.118	0.323	0.131	0.337	0.71
Islam	0.018	0.134	0.023	0.149	0.55
Other	0.148	0.355	0.136	0.343	-0.48
Socioeconomic status[(1)]					
socioecon1	0.094	0.291	0.11	0.313	0.84
socioecon2	0.167	0.373	0.208	0.406	1.85
socioecon3	0.611	0.488	0.545	0.498	-2.11
socioecon4	0.104	0.305	0.11	0.313	0.42
socioecon5	0.022	0.146	0.025	0.155	0.42
socioecon6	0.003	0.05	0.003	0.052	0.16
Marital status					
Married	0.873	0.333	0.903	0.296	1.05
Living together	0.031	0.173	0.026	0.158	-0.42
Never married	0.028	0.165	0.008	0.087	-0.89
Widow	0.013	0.114	0.011	0.106	-0.28
Divorced	0.055	0.227	0.052	0.222	-0.16
Children in family	2.67	1.022	2.654	1.194	-0.26
Culture parent1-child	0.009	0.093	0.011	0.106	0.6
Culture parent2-child	0.014	0.117	0.017	0.13	0.51

Note: See note from Table 1

We also present T-test statistics of the confounding variables after matching in Table 5, as to check for comparability. Recall that the Kernel matching estimator weighs the untreated students before matching them to the treated students in order to make them comparable (see Section 'Identification strategy' After applying these weights estimated by the Kernel density function with a bandwidth by Epanechnikov approximation, the independent T-test statistics show that treated

individuals are comparable to matched (i.e. weighted) untreated individuals with respect to their background characteristics. Compared with Table 2, all but one of the significant differences between students in the treatment and control group have disappeared owing to the matching. We conclude from these T-test statistics that the matching procedure has led to two very comparable groups that can be used for the remainder of the analysis. Because of the restrictions on common support, observations *who are not* on common support drop from estimation during the Kernel matching procedure. In our cases, only 12 observations (9 treated and 3 untreated individuals) were dropped from estimation, so that we now have 981 students in the control group and 1,054 students in the treatment group.

5.2. The return to gaining in-school work experiences

As follows, we will estimate the return to gaining in-school work experiences by four different specifications. First, we estimate the OLS regression. It does not take into account potential selection bias. Second, we estimate the return to gaining in-school work experiences for treated and matched untreated individuals on common support by using matching models (Rubin, 1974, 2006). Third, we rely on the Heckman (1979) selection model. And fourth, we also include individuals with an income who report not to be in paid labour.

With respect to the second specification, we use the non-parametric Kernel matching estimator (Rubin, 1974, 2006).

For the third specification, we use the Heckman selection model, and compare these results with our matched sample (i.e. the second specification), in order to show that our second specification also appropriately deals with the standard issues of selection into paid labour (see discussion above).

In the last specification, we relax the assumption that one has to be officially in paid labour to be included, and also include the individuals with other labour force statuses who still earn a wage, in order to directly correct for the wage of the censored observations that are removed by Heckman selection model.

Table 6 summarizes the results of the return to gaining in-school work experiences. The outcome variable is expressed as the log of hourly wages. All models include an extensive list of covariates (i.e. the models include the list of matching variables as control variables, too). Note that we obtain similar results without including covariates in the models, due to the matching procedure. The full model estimations are available at the authors on request. The estimate of interest is $\hat{\theta}$, known as the return to gaining in-school work experiences (i.e. the average treatment effect of the treated, ATT).

Table 6: Summary results of the return to gaining in-school practical experiences (outcome variable = log hourly wages)

	Model 1	Model 2	Model 3	Model 4
Return	0.1244*	0.1576***	0.1570***	0.2188**
	(0.0652)	(0.0454)	(0.0455)	(0.1068)
Covariates	Cscore	Cscore	Cscore	Cscore
	Gender	Gender	Gender	Gender
	Origin	Origin	Origin	Origin
	Age	Age	Age	Age
	Religion	Religion	Religion	Religion
	Socioeconomic status	Socioeconomic status	Socioeconomic status	Socioeconomic status
	Marital	Marital	Marital	Marital
	Siblings	Siblings	Siblings	Siblings
	Culture	Culture	Culture	Culture
				labour force status
Matching		Kernel	Kernel	Kernel
Caliper		0.01	0.01	0.01
Bandwidth		Epan	Epan	Epan
Specification	OLS	Matched Selection	Heckman Selection	Elaborated Selection
rho			-.9710	
			(0.0056)	
sigma			1.2680	
			(0.0826)	
lambda			-1.2312	
			(0.0848)	
Number of obs			2,035	2,035
Censored obs			876	
Uncensored Obs.	1,164	1,159	1,159	

Note: Robust standard errors between brackets. Star levels denote significant levels at (*) 10%, (**) 5% and (***) 1%.

In Model 1, the estimate of $\hat{\theta}$ is equal to 12.44 percent significant at the 10 percent level. This indicates that there is a positive return to gaining in-school work experiences: individuals with in-school work experiences earn, on average, 12 percent more on the labour market than their theoretical peers.

The ATT increases from 12.44 percent in Model 1 to 15.76 percent in Model 2 significant at the 1%-level. This estimate does not change in Model 3 ($\hat{\theta} = 0.157; \alpha = 0.01$). Comparing the results of Model 2 with Model 3, we find that the selection and matching approach produce almost identical results. These findings are in line with Guo and Fraser (2010).

Note that, compared to Model 2 and Model 3, the estimate of $\hat{\theta}$ in Model 1 is lower, and the standard error considerably higher. From this we conclude that not taking into account student self-selection into a practical or theoretical track yields an underestimation of the return to in-school work experiences.

We count 876 censored observations in total in Model 3. As previously explained in Section 'Identification strategy', these individuals are not officially in paid labour, and, therefore, are considered censored in Model 3. However, all of 876 censored observations in our data set do report an income owing to unemployment allowances, social security benefits, sidelines, or working at their parents' company. We consider individuals with side jobs, or working at parents' company, as being employed in the informal market. Only a small share of them has unemployment allowances or social security benefits.

We did not include individuals working in the informal market in Model 1 to 3, as, initially, we only considered being officially in paid labour as the rule of thumb. However, not including these individuals may bias the `true' return to gaining in-school work experiences, as the informal market may pay students with vocational specialization differently than theoretical students, and also differently than the formal market.

Before turning to the results of Model 4, we have to check whether these censored observations are significantly different on observed characteristics from the uncensored observations (cf. the balancing condition). Both the descriptive statistics of all confounding variables for the censored and uncensored observations separately (after matching), and the results of the independent T-tests, are available at the authors on request. Overall, we find that both types of observations are highly comparable, so that we conclude that the censored observations are not significantly different from the uncensored observations.

Next, we also check whether the balancing condition still holds for the censored observations only. Therefore, we conducted the independent T-tests (again, after matching) for censored and uncensored observations, separately. These results are also available at the authors on request. Based on the T-tests, we indicate that the treatment group and the control group remain very comparable on observed characteristics. The only significant T-tests are observed for age and ethnicity of the censored observations. We take both variables as controls into the regression. We conclude that the treatment and control group of the censored observations are highly comparable, and feel confident about including the censored observations into the regression.

The fourth model specification in Table 6 information on the set of censored observations. The results of Model 4 indicate that the estimate of $\hat{\theta}$ further increases from 15.76 percent to 21.88 percent, significant at 5 percent level. As such, by also considering individuals employed in the informal market, the coefficient increases with about 5 percentage points. Unlike earlier estimates of $\hat{\theta}$ that did not represent an interaction effect, model 4 presents the change in the difference in wages between treatment and control group when moving from the non-employed to the employed. Therefore, we also report the $\hat{\beta}$ coefficient from Equation (7), Section 'Identification strategy'. The estimate of $\hat{\beta}$ is equal to -5.8 percent not significant at 10 percent level. As such, we conclude that the 5 percentage points increase from model 3 to model 4 did not mean that the gap in wages amongst the employed has widened. The control group actually had higher income than the treated amongst the non-employed, but this is not significant.

Dustmann and Pereira (2008) offer a potential explanation for what is observed. The authors explored wage growth and job mobility in two Western European countries (UK and Germany). They argue that differences in wages between workers from different skill groups are partly ascribed to the way the labour market is organized (i.e. institutions, regulations, and training systems), and represented by unions. The more flexible the labour market is organized, the higher wage differences arise between qualified workers of various levels. This hypothesis is confirmed for the UK and Germany. The UK has a relatively flexible labour market, whereas Germany has strict regulations on wage tariffs by occupation. Dustmann and Pereira (2008) estimate a return to 10 years of labour market experience of about 80 percent for the UK, compared to only 35 percent for Germany. They explain that this relatively lower return for Germany is owing to workers with apprenticeship training, who earn high starting wages, but then have low wage growth.

The Dutch wage setting and apprenticeship system is more comparable to that of Germany than to that of the UK. In the Netherlands, about 20 percent of employees are union members, and wages are mostly set in collective agreements at industry or company level (Fulton, 2013). Contrary to Germany, however, the Dutch government takes several measures in order to support the establishment of a flexible labour market, and in particular, in order to increase job mobility by part-time and fixed-term contracts, internships, and temporary employment (called flex-workers). Following Dustmann and Pereira (2008), we argue that Dutch workers with in-school work experiences earn higher starting wages on the formal labour market than their theoretical peers. Low-educated individuals are more sensitive to labour market shocks, and have fewer opportunities to grow within a company or within a job. Recent numbers from the European Commission (Eurofound, 2012) confirm that a relatively high number of school-leaving youngsters with vocational

training are in temporary employment in the Netherlands. This makes them vulnerable on the labour market. For instance, older work-oriented students become more expensive for the company, or may be at the end of their growing curve within the company. Consequently, the employer may choose to replace them by newly graduated students with vocational specialization. Low-skilled vocational youth are then potentially at risk of becoming lifetime flex-workers.

6. Caveat

As a final robustness check, it is valuable to explore whether the results can be generalized, or whether it only holds for the particular groups who select into practical vocational courses. Therefore, it is proposed to estimate the average treatment effect for the non-treated (ATUT), essentially matching untreated to treated individuals. The results from this matching procedure are then compared to the obtained results presented in model 2, Table 6. Full model estimation output from the ATUT is available at the authors on request.

The ATUT indicate that not gaining in-school practical experiences decreases wages with 9.556 percent. These results are not significant at 5 or 10 percent level. We draw the same conclusion when using the Heckman selection model: not gaining in-school practical experiences insignificantly decreases wages with 7.343 percent. The coefficient of the ATUT that corresponds to Model 4, Table 6, is equal to -0.139, although still not significantly different from zero.

We did further analyses in order to indicate why we obtain the right sign (-9.556 percent) but not the significance when estimating the ATUT. The density of the propensity scores of the theoretical students is more spread (less dense within a chosen bandwidth) than the density of the propensity scores of the practical students. If, we specify a bandwidth above 0.2 the ATUT is equal to -11.48 percent and becomes significant at 10 percent level. Indeed, a broader bandwidth increases the potential choice set of finding a match for each treated student, as it is less restrictive. However, this chosen bandwidth exceeds by far the optimal bandwidth for doing an optimal Kernel matching (Haedler and Marron, 1985), causing potential threats for the common support. From the ATUT, we can conclude two things: (1) the ATUT is not as optimal for statistical inference as the ATT; and (2) vocational education with work experience is valuable for the sort of people who follow such courses, but it would not lead to a significant payoff for everyone.

7. Conclusion and discussion

We contribute to the literature on the return to schooling, in general, and the return to work experiences, in particular, by estimating the return to gaining in-school work experiences in the Netherlands. We estimate the return to in-school work experiences, and deal with the selection of individuals into different school tracks and into paid work by comparing Heckman (1979) selection model and Rubin (1974, 2006) matching model. The results from the selection model, and the matching model, are similar: workers with vocational specialization earn +16 percent higher wages than their theoretical peers. This estimate is significant at 1 percent level.

We further indicate that both the selection and matching models do not appropriately deal with censored observations in the presence of an informal market. The results show that, in case censored individuals are earning an income in the informal market, then the return to in-school work experiences increases from +16 percent to +22 percent significant at the 5 percent level.

The positive returns to gaining in-school work experiences confirm our hypothesis that students with vocational specialization have higher opportunity costs of staying in school than their theoretical peers. From these findings, we pose two contradictory (positive vs. negative) conclusions. First, work experience makes students more attractive on the labour market, and employers are willing to pay more for their skills. This may be considered desirable for school-leavers, as they can experience a better financial welfare owing to their educational choices. But it may also be desirable for employers, as they can find a better match between skill supply and job task requirements owing to vocational curricula (Mavromaras et al., 2012).

Second, the financial incentive that work-oriented students receive on the labour market is pushing students out of school at a relatively early point in the school career. This financial incentive is even higher in the informal market than in formally paid labour. From the literature, it is indicated that, despite the smooth school-to-work transition, those students with vocational specialization in particular face an increased risk of school dropout (i.e. leaving education without a higher secondary diploma), unemployment or a position in lifetime flexible employment (Cabus and De Witte, 2011; De Witte et al., 2013).

Further research should point out the effectiveness of labour market training programs for vocational youth, such as apprenticeships, dual tracks and National Vocational Qualifications (NVQ).

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Endnotes

[1.] Vocational education during secondary education is called pre-vocational education in the Netherlands. In this paper we use the term vocational secondary education to refer to the vocational school career in secondary education. A student can decide to enroll in continued vocational education after graduation from pre-vocational education. Throughout this paper, the scope of focus is pre-vocational education (vocational secondary education). As such, we consider choosing continued vocational education, for instance, in combination with being in paid labour, also as a labour market outcome.

[2.] Given the large variation in hourly wage, we also did the matching and ran the analyses when we excluded the lowest 25 and 70 observations with respect to wage. These analyses have led to very similar results with respect to both magnitude and significance.

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Why Do School Dropout Rates Vary (So Much) Across Countries? – A Survey

Sofie Cabus

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Abstract

This chapter brings together the findings from various sources of academic literature and empirical- and statistical evidence in order to answers the question *"Why do school dropout rates vary (so much) across advanced- and developing countries?"* Answers to this question are sought by using the following sub-questions: *(1) What is the definition of school dropout? (2) How big is the problem of school dropout (in advanced- and developing countries)? (3) What determines, or 'triggers', school dropout?* These questions are answered by using post-2010 academic literature on school dropout, published in peer-reviewed journals, and covering both advanced- and developing countries. The key findings are summarised as follows. First, close inspection, of definitions stipulated in post-2010 articles, reveals that it is possible to identify explicitly, but also implicitly, three ingredients: (1) a minimum level of education; (2) a relevant age-group; and (3) those persons who are excluded from calculations. In particular the latter two ingredients can vary (a lot) across studies and official statistics and it does matter for the level of published school dropout rates. Second, although there is large heterogeneity in the level of dropout rates observed across countries, a fairly steady downward sloping trend of the school dropout rate is observed over the past 15 to 25 years for almost all countries over the world. And third, albeit the large set of studies on school dropout determinants, there is still much unknown in the academic literature on the most effective approach for keeping students in school in order to lead them towards a high school diploma. This is mainly because research on the most effective way to tackle early school -leaving was (is) absent.

Keywords: Determinants; Definition; Literature Review; International Comparison; School Dropout;

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1. Introduction

Given the costs arising from early school leaving, for both the individual and the society, government officials and policymakers from advanced economies are increasingly interested in the complex problem of school dropout and, moreover, how to reduce it (Lamb and Markussen, 2010; Anspal et al., 2011; European Commission, 2013; US Department of Education, 2016; Brunello and De Paola, 2014).[30] While scientific research on (cost-effective approaches for) school dropout is mainly dominated by advanced economies (Section 4), early school leaving policy also attracts the attention of stakeholders in developing countries. Glewwe and Muralidharan (2015, p.2) indicate that: *"*[Government] *spending, along with several other factors, has led to large increases in school enrollment at all levels in the past 25 years. Indeed, most children in developing countries now complete primary school and obtain at least some schooling at secondary level."*

Notwithstanding the ostensible problem of school dropout in low-income countries, at least, when compared to advanced countries, much research and policy questions on educational attainment are similar. Therefore, questions that can unravel the complexity and dynamics of the school dropout problem can be answered for developing- and advanced countries alike. In general, education research identifies the determinants of student (non-) attendance and dropout in order to answer the question of how to keep students in school. In this respect, the previous literature indicates that school dropout is most prevalent among male adolescents who live in poor neighbourhoods and are negatively influenced by home- and neighbourhood factors (e.g. rather low educational attainment of parents; poverty; having bad friends; drugs and alcohol abuse; sexual risk behaviour and teenage pregnancy and marriage) or school factors (e.g. the socio-economic composition, the teacher-students ratio; teachers' absence or instructional quality); among other determinants (Rumberger and Rothermund, 2012; De Witte et al., 2013).[31]

[30] Belfield (2008) categorizes these costs associated with early school leaving as: (1) private costs; (2) fiscal costs; and (3) social costs. Private costs are those costs for the individual arising from foregone earnings and increased risks on unemployment, but can also be expressed in terms of non-monetary outcomes like increased health risks (Albouy and Lequien, 2009); or reduced happiness (Oreopoulos, 2007).[30] Foregone income leads to decreased tax revenues, and, as such, fiscal losses for society (Psacharopoulos, 2007). This makes up the second category of fiscal costs. It also includes government expenditures on unemployment insurance and public assistance (Belfield, 2008). Finally, two examples of social costs, the last category, are juvenile delinquency and reduced knowledge on good citizenship (Belfield, 2008; Lochner, 2011).

[31] An overview of academic research on school dropout determinants published before 2010 for advanced economies is provided by De Witte et al., 2013; and for developing countries by Glewwe and Muralidharan, 2015.

Albeit the large set of studies on school dropout determinants, there is still much unknown in the academic literature on the most effective approach for keeping students in school in order to lead them towards a high school diploma. This is mainly because research on the most effective way to tackle early school -leaving was (is) absent. There is a notable shift in the past 5 to 10 years from more descriptive and correlational studies towards evidence-based and cost-effective education policy (Cabus, 2013). It is the aim of these studies to identify effective (policy- or school-initiated) interventions that decline school dropout rates. As will become clear from this chapter, despite the shift in academic (economics of) education research towards causal evidence, there is still much unknown and not examined when it comes to 'what works' in the fight against school dropout.

In particular, the discussion of post-2010 scientific articles in Section 4 reveals that education research still focusses on the process and dynamics underlying school dropout rates, as such, the school dropout determinants, but to much lesser extent on effective approaches on how to deal with students who are at-risk to drop -out at school. Moreover, academic research often 'sticks to' home-, neighbourhood-, and school-related determinants, while one can clearly identify a strong link between, on the one hand, school dropout, and, on the other hand, employment opportunities and wages on the labor market, and the general economic climate (Section 4.6). Country-level institutions are deterministic for the way a country organises its educational provision and facilitates the transition from education to the labor market, and, hereby, also influence the nationally observed school dropout rate.

This chapter brings together the findings from various sources of academic literature and empirical- and statistical evidence in order to answers the question *"Why do school dropout rates vary (so much) across advanced- and developing countries?"* Answers to this question are sought by using the following sub-questions:

- What is the definition of school dropout?
- How big is the problem of school dropout (in advanced- and developing countries)?
- What determines, or 'triggers', school dropout?

These three questions are coherent. First, cross-country comparisons require a definition of school dropout that is comparable across countries. This seems already available from the literature and ready to use, but, in fact, it is not. Section 0 discusses a framework for estimating internationally comparable school dropout rates, and, using this framework, Section 3 constructs a new dataset consisting of

harmonised dropout rates for a set of 49 developing countries. Using multiple data sources, the level of the school dropout problem is discussed along with some reasons for why (big) differences between low-income- and advanced countries are observed. This provides an answer to the second question of *'how big is the problem of school dropout?'* Third, aggregate-level statistics mask the underlying micro-level determinants of school dropout. Based on country-level dropout rates, one cannot tell who is most at-risk of school dropout. Differently put, it refers to the question: *'the dropout population in my country consists of whom?'* This is particularly a relevant question for policy makers who wish to reduce the country-level dropout rate with targeted policy. Section 4 outlines the determinants of school dropout in line with an elaborated framework of Rumberger (2001, 2011), at various levels of the problem, and by using post-2010 literature. Furthermore, I add to this framework by establishing the economic determinants of school dropout. Section 5 concludes.

2. What is the definition of school dropout?

2.1. Three ingredients

Throughout this chapter, the terms high school diploma and upper secondary diploma will be used interchangeably in order to denote successful graduation from education or training that leads to a certificate of level ISCED-3 (other synonyms: 'school success'; 'retention to the final year'; or 'school completion').[32] Moreover, 'early school leaving', 'leaving education early', and 'school dropout', will be used interchangeably in order to denote leaving education before successful graduation. Lamb and Markussen (2010) indicate that one can find many synonyms in the previous literature for school completion or school failure, mainly due to the different terminology used across countries, districts or states. However, these concepts do not necessarily measure school dropout rates in the same way. One who wishes to study early leaving from education or training, therefore, should first consider its definition.

[32] The International Standard Classification of Education (ISCED) was developed in the 1970s in order to facilitate international comparisons of different education statistics and indicators with regard to education programs or qualifications (certificates) by levels and fields. The latest updates of ISCED took place in 1997 and 2011 (more information can be obtained at *uis.unesco.org*).

Table 13: Definitions of and data for school dropout in selected scientific literature

First author	Year	Definition/data	Page
Anderson	2014	A binary indicator that is equal to 1 if the respondent is a high school dropout. No further definition specified. The author uses IPUMS data 1980, 1990, and 2000 Censuses.	(Note1)
Baird	2010	*"A baseline 'dropout' was any girl or young woman, who was out of school at baseline - regardless of how long she had been out of school before the study as long as she had never been married and was between the ages of 13-22."* The authors use longitudinal survey data of 2893 young women. There were two survey rounds in total, one baseline and one follow-up survey.	p.59
Cabus	2011, 2013, 2015	*In the empirical analysis, the author defines school dropout as: "A youngster below the age of twenty-three who was enrolled in school on 1 October of a given year, but who is not enrolled in the following year on 1 October, and who has not* obtained *a higher secondary certificate."* The authors use administrative data of all registered students in formal education in the Netherlands.	p.1388; p.605; p.72
Cabus	2012	Data are retrieved from eurostat, the European Statistical Agency (European Commission). The underlying data are from the European Labour Force Survey. The European Commission defines a school dropout as a student without a higher secondary diploma and who is not further enrolled in education or training between the ages 18-24 years.	p.775
Cabus	2016	"An early school leaver (or school dropout) is a youngster below the age of 23 who leaves education without a higher secondary certificate." The authors use longitudinal survey data of 4,000 Dutch vocational students (VOCL'99) who enrolled in secondary education in 1999-00.	p.1
Chevalier	2013	The authors use data from the UK Labour Force Survey (LFS) 1993-2012. Then, the authors look at *"the decision to participate in post-compulsory schooling, defined as a dummy equal to one if the 16 to 18 year old child is either in post compulsory education at present or was in education between 16 and 18 but had left school by the time of interview."*	p.5
Cho	2011	No definition for school dropout specified. The authors collected own data by using surveys among 105 students aged 12-14 years who had lost one or both parents through death by any cause.	p.524
Crowder	2011	Longitudinal data from the Panel Study of Income Dynamics (PSID) are used in order to construct the dependent variable school dropout. It denotes *"a binary indicator of whether the PSID participant had graduated from high school or received a GED by 25 […]"*	p.92
De Witte, Cabus	2013	"School dropout has been defined as leaving education without obtaining a minimal credential (most often a higher secondary education diploma)." Furthermore, the authors also refer to the OECD definition: "[…] on average, 72% of all 24- to 34-year-olds had completed a year 12 equivalent in 1999."	p.14

De Witte, Csillag	2013	"School dropout is defined as youngsters (below age 23) who leave secondary education without a higher secondary degree." The authors use data on all registered students in Amsterdam between the ages 13-18.	p.552
De Witte, Nicaise	2013	The authors distinguish between two definitions commonly used by the European Statistical Agency (eurostat): 'early leavers from formal education' and 'early leavers from education and training'. Whereas the former definition only restricts calculations to students enrolled in formal education, the latter definition also considers those persons enrolled in non-formal education as not being dropped out at school.	p.334
Fall	2012	"Almost one-third of all public secondary students in the United States each year dropout of school." No further definition specified, however, the authors refer to not completing high school within the context of school dropout.	p.787
Gasper	2012	The authors use surveys (NLSY97) and the school dropout status was derived from youth self-reports of school enrollment at each time the survey was taken. "Dropout is defined as any youth who is not enrolled in school and who does not have a high school diploma at the time of round 7 interview, when the youth are between ages of 19 and 22. Youth who obtained a GED are counted as high school dropouts in the analysis [...]"	p.497
Grant	2010	No definition for school dropout specified. Within the context of less developed regions, the authors refer to *"[…] school attainment, as measured by grades of school completed."* Data on developing countries from the Demographic and Health surveys are used.	p.87
Haelermans	2015	The authors measure school dropout below age 19. Registration data are retrieved for all students in secondary education in the Netherlands between 2005 and 2010. The data consist of a binary indicator for school dropout (1 if yes) that has been constructed by the administration office.	p.355 and p.360
Henry	2012	No definition for school dropout specified. The authors aruge that *"Once youth dropout of school, they leave the control of the school environment and they are often difficult to reach in the community. As a result, it is a challenge to provide appropriate services to them and their families."* The authors use a longitudinal panel of 1,000 students who enrolled in 7th and 8th grade in 1988.	p.157
Hill	2010	No definition for school dropout specified. The authors refer to statistics of US Department of Commerce (2000) and indicate that *"[…] only 64% of Latino 18-24-year-olds have completed high school […]"* The authors use mainly qualitative data.	p.96
Lavrijsen	2015	Data are drawn from the 2009 ad hoc module of the European Union Labour Force Survey on Entry of Young People into the Labour Market. School dropout is defined as *"a person who has left the formal education system without having acquired a qualification of at least ISCED level 3."* Furthermore, the authors collect data for respondents aged 20-30-year-olds.	p.300
McCaffrey	2010	No definition for school dropout specified. The authors collected information from both school staff reports and student self-reports in order to create the dependent variable	p.1287

		high school dropout status.	
Mora	2011	No definition for school dropout specified. The authors look at 'intention to dropout'. Data were collected by using surveys among Catalan students.	p.576
NcNeal	2010	The authors use NELS:88 data. They only keep public-school students in the sample who were in the second and third waves of the study (10th and 12th grade). Furthermore, the authors indicate *"[...] the percentage of the population between ages 16 and 19 who are high school dropouts."*	p.10
Ou	2010	The author retrieved data from the New Jersey Department of Education in order to combine information on test scores of the high school exit exam with background characteristics of the student. No definition for school dropout specified, however, the author uses a couple of exclusion criteria: the analysis solely focusses on students attending public schools. The author also deleted migrants and students with less than one year of student attendance from the sample.	p.174
Rumberger	2012	No definition for school dropout specified. The authors refer to calculations presented in *Education week*, hereby indicating that high school dropouts fail to earn a high school diploma.	p.491
Song	2012	Data from NELS:88 are used, a nationally representative sample of high school students. *"The dependent variable in the study is the odds of dropping out of high school between 1988 and 1992. […] The year that respondents report dropping out of high school is the measure of time."* As such, we conclude that school dropout status is a self-reported measure.	p.23
Traag	2011	No definition for school dropout specified. The authors use a longitudinal survey (VOCL'89) in order to retrieve data on grade repetition and school dropout. They classify students who do not have a diploma at all, or ISCED2 or lower, as school dropouts.	p.50
Wodtke	2011	*Longitudinal data from the Panel Study of Income Dynamics (PSID) are used in order to construct the dependent variable school dropout. "The oucome measure of interest in this study, high school graduation, is measured at age 20 […]."* No further definition for school dropout specified.	p.719

Note 1: Supplementary material in online Appendix.

Table 13 summarises the definitions and data sources for school dropout used in a selected set of post-2010 scientific studies (Section 4). Practically, all definitions underlying the empirical studies (among others, see Anderson, 2014; Cabus and De Witte, 2011, 2016; Crowder and South, 2011; Gasper, 2012; McCaffrey et al., 2010) create a binary indicator for school dropout based on a set of criteria with 1 equal to ‘yes (I am)’ and 0 ‘no (I am not)’. However, close inspection of these definitions reveal that it is possible to identify three ingredients: (1) a minimum level of education; (2) a relevant age-group; and (3) those persons who are excluded from calculations.

First, a person leaves education early when the highest educational attainment level is equal to or below lower secondary education (ISCED-2). There is high consensus about this first ingredient across all scientific studies. However, it should be noted that, depending on the country concerned, a person can obtain a valid (or equivalent) diploma at different ages and that the graduation age does not always coincide with the compulsory education age (Section 3).[33] Gasper (2012) considers persons who obtained an equivalent diploma (GED) in the US also as high school dropouts, mainly because GED credentials lead to the same labour market outcomes as dropouts. Doing so, Gasper (2012) is not in line the US National Center for Education Statistics (NCES) that argues that those youth who eventually received an equivalent diploma (GED), are not defined as early leavers from education and training.[34]

Second, the definition mentions a relevant age-group in which school dropout should be measured. From Table 1 it is clear that there have been many different age groups used across the studies. This is mainly due to data availability and limitations. Studies using (LFS) data from European Statistical Agency (Eurostat) in order to calculate school dropout rates look at 18- to 24-year-olds in line with the definition of the European Commission[35] (Cabus and De Witte, 2012; De Witte, Nicaise et al., 2013). However, some European studies also look at students aged 18 and below in order to avoid inaccurate measurement of school dropout in registration data. For example, Cabus and De Witte (2015b) and Haelermans and De Witte (2015) argue that schools infrequently report absence and dropout behaviour of students to the administration office because 18-year-olds students are already beyond the compulsory education age.[36] Henry, Knight, and Thornberry (2012) add that: "*Once youth dropout of*

[33] Lamb and Markussen (2010) argue that obtaining a high school diploma does not mean unequivocally the same thing across countries. For example, a diploma in US, Canada, and Sweden can provide access to university and vocational higher education, while in the Netherlands only an upper secondary diploma from the highest ability track provides straightforward access to university.

[34] The US Department of Education defines school dropout as *"[…] the percentage of the civilian noninstitutionalized 16- to 24-year-old population who are not enrolled in school and who have not completed a high school program, regardless of when they left school* (https://nces.ed.gov/programs/digest/d14/)*."*

[35] The European Commission argues that school dropouts are *'young people* [18-24] *who leave education and training with only lower secondary education or less, and who are no longer in education or training*' (European Commission, 2013, p.8).

[36] Using 25+ as the relevant age-group can also be beneficial for statistical analysis, as one reasonably can expect that the likelihood to obtain a secondary diploma above the age of 25 reduces to almost zero (Glewwe et al., 2011). For example, UNESCO looks at educational attainment 'at least completed upper secondary (ISCED 3 or higher)' among the population aged 25 and older (data.uis.unesco.org). As such, it may provide more accurate numbers on the 'stock of human capital' in a population (or else, the educational composition of the labor force). However, it should be noted that rates of school dropout are then far higher than those presented in Table 2, as older generations were less likely to obtain high school diplomas when they were young than younger generations nowadays. Furthermore, for estimations of the effectiveness of dropout prevention programs aiming at school

school, they leave the control of the school environment and they are often difficult to reach in the community (p.157)." As such, registration data from schools may lack accuracy because teachers or principals often do not know the (education and labour market) status of these students. On the contrary, surveys like the Panel Study of Income Dynamics (US) and the Labour Force Survey (EU) can reach young people in- or out-of-school and ask them retrospectively about their educational attainment and dropout behaviour (e.g. Chevalier et al., 2013; Lavrijsen et al., 2015; McCaffrey et al., 2010). When taking a 'snapshot' of school dropout, for example, at the age of 25, it is argued that most students, by then, will have obtained the secondary education diploma, or not. This minimalizes the measurement error due to the fact that, at earlier ages, people still can enroll in school again and obtain the diploma (De Witte et al., 2013; for a discussion, see Section 3). Nonetheless, the main disadvantage of using surveys is the self-report bias, for example, respondents may tend to overestimate the 'true' years of schooling or misreport on their dropout status (e.g. Brunello and De Paola, 2013).

Third, some definitions exclude particular groups from calculations, for example, by using the words '*no longer* in education or training' (ec.europa.eu/eurostat), 'formal versus non-formal education or training' (De Witte, Nicaise et al., 2013) or '*noninstitutionalised* 16- to 24-year-old population' (NCES, US Department of Education). Especially for developing countries, this last ingredient can be very important because of the relatively high number of out-of-school children or because of those who received their education at home (Section 3.2). Most authors[37] included in Table 1, however, do not formulate a definition for school dropout using this third 'exclusion' ingredient, even though the data underlying their empirical analysis are affected by it. The Panel Study of Income Dynamics, the European Union Labour Force Survey, and National Education Longitudinal Study, are not representative for, for example, institutionalized people (e.g. Cabus, 2015; Crowder and South, 2011; Gasper, 2012; Lavrijsen et al., 2015), or focus only on students attending public schools (McNeal, 2010), or even exclude migrants from analysis (Ou, 2010).

2.2. Towards harmonised school dropout rates

A definition that stipulates three ingredients is attractive, as statisticians all over the world are then able to compute the dropout rate with a consensus across countries on 'when a person leaves education too

going youth, 25 year olds and older cannot be used as the relevant age-group (as they were not in school at the time of implementation of the prevention programs).

[37] Only Crowder and South (2011) and Gasper (2012) formulate whether they exclude persons with GED credentials from analysis.

soon'. Notwithstanding the consensus on the ingredients, every country is free to choose the relevant age-group and the persons who are excluded from the measurement of school dropout. This makes international administrative data largely incomparable (see also Lamb and Markussen, 2010). It is then difficult to answer how big the school dropout problem is, as some countries can 'polish' their dropout rates, for example, by excluding difficult-to-reach persons from calculations (i.e. ingredient 3), while others do not perform this practice. This is not always visible at first -sight. Furthermore, given the multiple definition and data sources used by the authors, there is no critical value in academic research that assesses a dropout rate as high or low.

In fact, a possible solution to this problem of incomparability across countries has been given at supra-national policy level. In this respect, one may think of the European Union Lisbon 2000- and the Horizon 2020 framework. First, dropout rates for each European Union Member State all come from one data source, namely: the European Union Labour Force Survey (EU LFS). This household sample survey is conducted in the 28 Member States of the EU, and also in Iceland, Norway and Switzerland. The national statistical institutes are responsible for the collection of the data and, then, these data are deposited centrally at Eurostat, the Statistical Agency of the European Commission. Aggregate statistics at the country-level for school dropout are presented free of charge on the World Wide Web at *ec.europa.eu/eurostat*. Second, Lisbon 2000 and Horizon 2020 indicate what is a high- or a low country-level school dropout rate by using benchmarking (i.e. a relative rank of countries from lowest to highest dropout rate) and a target. Among other things, the European Council has argued back in 2000 that the dropout rate across EU-countries should reduce with 50 percent to a maximum of 10 percent through policy interventions (European Commission, 2013). This target was not achieved by many European Union Member States by 2010, and, therefore, has been included again in Horizon 2020 (ec.europa.eu/europe2020).

There are big advantages of having supra-national frameworks like Horizon 2020.[38] Owing to uniform data and definition, changes in dropout rates can be easily compared between countries in order to name the best performing country, and shame the worst performing country, with respect to reaching the headline target of 10 percent. In this respect, Cabus and De Witte (2012) provide a naming and

[38] Note that the US has its own framework ('No Child Left Behind Act') stipulating that at least 90 percent of the population should obtain a high school diploma. Canada and Australia adopted similar frameworks.

shaming analysis for the school dropout performance of EU-12 countries.[39] They argue two main things: (1) One should account for the different starting positions, and the different economic situations or systems that are not easily altered in the short-term, in order to correctly apply benchmarking of cross-country performance. Not every observed decrease in the dropout rate is owing to targeted policy interventions, but can also be the result of, for example, an economic recession.[40] And (2), between 2000-2008, owing to policy interventions school dropout was tackled most effectively in Luxemburg and the Netherlands. Contrary, Portugal and Spain did not succeed in effective policymaking.

There are also disadvantages of using supra-national policy frameworks. Suppose, for example, that country A has a comparative advantage in the production of output that embodies a high-skill-mix, while country B has a comparative advantage in the production of output that embodies a low-skill-mix. These big differences in skill-mix between countries particularly hold when also considering the dropout rate of developing economies. Differently put: is it a big problem for policymakers of country B when the dropout rate exceeds 10 percent? The answer to this question is ambiguous. On the one hand, one can argue 'no, it is not a big problem' because high dropout rates facilitate allocative matching efficiency of workers to vacancies in Country B when the demand for low-skilled is high. On the other hand, from the perspective of welfare and well-being of the individual, one can argue 'yes, it is a big problem' because, irrespectively of the country concerned, and assuming that education is a normal good, high dropout rates indicate a lot of individuals living in poverty, who have no access to education, and who have lifetime disadvantages on the labour market.[41] In particular, supporters of the human capital hypothesis (Becker, 1962), arguing that schooling can lead to better outcomes on the labor market will adhere to this second answer. On the contrary, proponents of signaling and screening theory (Spencer, 1972), arguing that everyone will get that amount of schooling that fits their ability in order to signal 'true' productivity, will rather adhere to the first answer.

[39] EU-12: Austria, Belgium, Denmark, Finland, France, Germany, Luxembourg, Netherlands, Portugal, Spain, and Sweden.

[40] Cabus and De Witte (2012) provide evidence that wages (i.e. the opportunity cost of schooling) are positively correlated with school dropout rates, while economic advancement (as measured by per capita GDP) is negatively correlated with school dropout rates.

[41] In Country B, it may well be that poor schooling is the result of not being able to pay for education and improve living conditions (e.g. Behrman, Segupta and Todd, 2001; Todd and Wolpin, 2006).

3. How big is the problem of school dropout?

3.1. Statistics for advanced countries

Table 2 summarises non-harmonised school dropout rates for advanced countries. The table provides information on the relevant age-group in the heading of the columns. The source of the data is given below Table 2. It is proven to be difficult to find dropout rates (or, the reverse, completion rates) for the year 2015 for all advanced countries.[42] As dropout rates do not fluctuate substantially over the years, but rather tend to follow a downward sloping trend, a five-year window is not considered so problematic as the differences in measurement of school dropout rates across countries.

So, how big is the problem of school dropout in the selected advanced economies *based on the non-harmonised official statistics*? In Australia, 26 percent of students drop -out by the age of 19 in 2015. Leaving aside the difference in definitions and years of measurement, all other advanced countries in Table 2 perform far better than Australia, with the only exception of New Zealand. Here, 25.3 percent of students aged 15-24 dropped out in 2011. The dropout rate in the US is equal to 6.8 percent in 2013. Hereby, the US (6.8 percent, 2013) is ranked fifth after Japan (3.4 percent, 2016), Switzerland (5.4 percent, 2014), Luxembourg (6.1 percent, 2014), and Sweden (6.7 percent, 2014). To conclude, the average school dropout rate for the selected group of advanced countries is estimated at 12.5 percent with a standard deviation of 8.3.

[42] In Japan, the enrollment and advancement rate (instead of the dropout rate) is calculated as the percentage of new graduates from upper secondary school from the total group of upper secondary school enrollees. Statistics Japan also present the percent share of graduates who advance to tertiary education, or to employment.

Table 14: School dropout rates (%), compulsory school age (years) and duration of primary and secondary education (years) in advanced economies

		Age-group								
Country	Year	18-24	16-24	By age 19	20-24	% of tot. enrolled	15-24	School Age	Duration	GDP per capita
Australia	2014			26				11	13	61,980
Austria	2014	7						9	12	51,122
Belgium	2014	9.8						13	12	47,328
Canada	2012				7.8			11	12	52,087
Denmark	2014	7.8						10	12	60,718
Finland	2014	9.5						10	12	49,843
France	2014	9						11	12	42,726
Germany	2014	9.5						13	13	47,774
Greece	2014	9						9	12	21,673
Iceland	2014	19.1						11	14	52,037
Ireland	2014	6.9						10	13	54,339
Italy	2014	15						9	13	35,223
Japan	2014					3.4		10	12	36,194
Luxembourg	2014	6.1						10	13	116,613
Netherlands	2014	8.7						13	12	52,139
New Zealand	2011						25.3	12	13	37,897
Norway	2014	11.7						11	13	97,300
Portugal	2014	17.4						9	12	22,124
Spain	2014	21.9						11	12	29,722
Sweden	2014	6.7						10	12	58,899
Switzerland	2014	5.4						9	13	85,617
Turkey	2014	38.3						9	11	10,515
United Kingdom	2014	11.8						12	13	46,297
United States	2013		6.8					12	12	52,980

Note 1: ec.europa.eu; figures come from the European Union Labour Force Survey and refer to the year 2014
Note 2: nces.ed.gov; figures come from US Department of Education, National Center for Education Statistics, NCES, 2015, and refer to the year 2013
Note 3: mitchellinstitute.org.au; Lamb, Jackson, Walstab and Huo (2015), *Educational opportunity in Australia 2015: Who succeeds and who misses out*, Center for International Research on Education Systems, Victoria University, for the Mitchell Institute, Melbourne: Mitchell Institute.
Note 4: statcan.gc.gv; figures come from the Labour force Survey of Statistics Canada and refer to the year 2011-12
Note 5: mext.go.jp; statistics on enrollment and advancement rates in Japan published by the Ministry of Education, Culture, Sports, Science and Technology, 2016, and refer to the year 2014.
Note 6: stats.govt.nz; figures come from Statistics New Zealand and refer to the year 2011
Note 7: UNESCO education database
Note 8: World Bank for GDP, per capita (current $US)

3.2. Statistics for developing countries

It is proven difficult to present official school dropout rates for developing countries. Measures of educational attainment, enrollment, and completion rates, are presented for a considerable group of developing countries in international datasets (e.g. UNESCO; Education Statistics from World Bank; Barro and Lee, 2013). However, there are limitations for using these data. Besides those data limitations already discussed in Section 0, Krueger and Lindahl (2000) argue that measurement error cannot be neglected when using international datasets on educational attainment.

For this purpose, I have collected information from the Demographic and Health Surveys (DHS) over the period 1990 to 2014 for 49 developing countries, 173 surveys, or 4.1 million unique observations (for more information, see www.measuredhs.com). Although the household survey aims at gathering information on demographic and health related issues, it also contains basic information on education. This is available for each household member that participated in the survey. A database with (basic) information on enrollment in school, school attendance, educational attainment, graduation status, dropout status, preferably all measured at the level of the individual student (like EU LFS), facilitates international comparisons, because one can uniformly agree on the three ingredients for every country included in the data. For DHS, these three ingredients are stipulated as follows. (1) From the combination between highest level of educational attainment (no education; incomplete primary; primary; and incomplete secondary education), and the dummy variable for enrollment status of the respondent in the year of the survey, we construct an indicator for school dropout for each household member. (2) School dropout statistics are estimated at the individual-level, and then aggregated for the relevant age- group 18-24 (making them comparable to estimates of EU LFS). (3) In line with previous official definitions on school dropout rates for advanced countries, I exclude out-of-school children and home education from both the numerator and denominator.

Table 3 presents dropout rates from primary and secondary education among the young population aged 18-24 for 49 developing countries. The output refers to the latest survey done for the country concerned, and the year for each country is presented in the second column of the table. School dropout rates for the other survey years of the 49 countries are available from the author on request. On average, statistics are reported for the year 2010, with the earliest year 1996 and the latest year 2014. For completeness, Table 3 also presents the estimated population of out-of-school children (i.e.

those youngsters with 'no schooling'), and the average years of schooling of those youngsters who ever enrolled in formal education and completed at least 1 year of schooling.

Table 15: School dropout rates (%) at primary and secondary education among people aged 18-24, compulsory school age (years) and duration of primary and secondary education (years) in developing countries

Country	Year	No schooling	Incomplete primary	Incomplete secondary	Years of schooling	School age (2)	Duration (2)	GDP per capita (3)
Armenia	2010	0.2	0.0	7.0	11.5	11	10	3,125
Bangladesh	2014	8.4	15.1	65.4	7.8	5	12	1,087
Benin	2011	35.2	21.4	73.0	8.8	6	13	799
Bolivia	2008	0.7	16.2	35.8	10.7	8	12	1,737
Brazil	1996	4.4	13.4	70.4	7.2	7	11	5,145
Burkina Faso	2010	58.9	32.4	91.4	7.2	10	13	574
Cambodia	2014	5.0	25.2	79.8	7.9	-	12	1,095
Cameroon	2011	10.9	16.5	82.7	8.4	6	13	1,259
Chad	2004	54.6	41.3	91.1	6.3	6	13	455
Colombia	2010	0.2	5.7	31.1	10.1	10	11	6,251
Congo	2011	4.0	14.1	81.4	8.8	10	13	2,259
Congo, Dem. Rep.	2013	7.5	17.9	69.6	8.5	8	12	414
Cote d'Ivoire	2011	38.3	28.3	79.1	8.1	10	13	1,232
Dominican Republic	2013	2.5	14.4	37.8	10.5	6	12	5,969
Egypt	2014	5.7	4.6	26.1	11.0	8	11	3,366
Ethiopia	2011	45.0	34.8	82.8	6.0	6	12	356
Gabon	2012	3.3	7.1	79.0	9.1	6	13	10,642
Ghana	2014	7.6	8.7	61.5	10.5	9	12	1,442
Guinea	2012	40.3	19.4	75.6	8.7	6	13	487
Haiti	2012	4.2	21.5	85.6	7.7	6	13	767
Honduras	2011	2.6	16.8	69.2	8.6	6	11	2,324
Indonesia	2012	0.0	5.0	45.0	10.4	9	12	1,861
Jordan	2012	1.2	1.5	40.5	12.1	10	12	4,897
Kazakhstan	1999	0.5	0.3	14.1	10.8	11	11	1,130
Kenya	2014	3.5	14.8	53.1	9.7	8	12	1,358
Kyrgyzstan	2012	0.5	0.3	13.9	11.9	9	11	1,178
Lesotho	2009	4.7	26.8	80.1	8.1	7	12	860
Madagascar	2008	17.6	50.4	93.0	5.4	9	12	472
Malawi	2010	6.3	51.2	83.7	7.2	8	12	366
Mali	2012	57.4	23.5	82.8	8.2	7	12	642
Morocco	2003	29.4	30.1	82.5	8.0	6	12	1,650
Mozambique	2011	13.2	46.4	92.5	6.6	7	12	525

Country	Year	No schooling	Incomplete primary	Incomplete secondary	Years of schooling	School age (2)	Duration (2)	GDP per capita (3)
Namibia	2013	4.4	9.2	59.7	9.7	10	12	5,435
Nepal	2011	15.0	12.3	47.8	8.3	5	12	696
Nicaragua	2001	12.2	26.2	68.8	7.7	6	11	1,044
Niger	2012	64.1	41.0	95.5	6.7	7	13	394
Nigeria	2013	25.2	2.9	29.5	10.3	9	12	2,980
Pakistan	2012	27.9	9.4	47.0	8.8	5	12	1,266
Peru	2000	1.5	8.5	33.9	9.9	11	11	1,967
Philippines	2003	1.2	8.9	31.9	9.9	7	10	1,011
Rwanda	2010	7.2	55.3	91.6	5.6	6	12	554
Senegal	2010	46.6	33.8	87.7	7.7	6	13	998
Sierra Leone	2013	29.7	10.8	66.4	8.9	6	12	783
Tanzania	2010	13.5	14.7	97.3	7.5	7	13	709
Togo	2013	12.9	21.2	82.1	8.2	10	13	626
Turkey	2003	5.4	2.9	54.2	8.8	9	11	4,587
Uganda	2011	4.9	40.2	87.0	7.6	7	13	591
Zambia	2013	3.6	17.8	72.6	8.6	7	12	1,759
Zimbabwe	2010	0.9	7.8	90.1	9.7	7	13	674

Note 1: Own calculations from Demographic and Health Surveys
Note 2: UNESCO education database. 'School age' denotes the total theoretical years of compulsory schooling, and 'Duration' denotes the total theoretical years of primary and secondary education together.
Note 3: World Bank for GDP, per capita (current $US)

So, how big is the problem of school dropout in the selected developing economies based on harmonised school dropout rates? Armenia (7.0 percent), Kyrgyzstan (13.9 percent), Kazakhstan (14.1 percent), Egypt (26.1 percent) and Colombia (31.1 percent) have the lowest dropout rates among the selected group of developing countries. Contrary, Madagascar (93.0 percent), Mozambique (92.5 percent), Burkina Faso (91.4 percent), Chad (91.1 percent) and Haiti (85.6 percent) have the highest dropout rates. The average dropout rate for the 49 developing countries is equal to 64.3 percent with a standard deviation of 25.6. As such, in general, school dropout rates for developing countries are substantially higher than for advanced countries.

Comparing figures across countries at face value begs the question of whether an absolute level of education (e.g. upper secondary) is a suitable benchmark for all countries. Moreover, some education systems introduce specialization at an earlier stage than others, and some have distinct vocational streams while others do not (Shavit and Müller, 1998). This brings about qualitative issues that may

hamper cross-country comparisons of school dropout rates. In this respect, several points of discussion are outlined as follows.

3.3. Advanced economies compared to low-income countries

There are (at least) three 'logical' explanations for why school dropout rates are high in some developing countries compared to what is seen in most advanced countries. (1) The compulsory education age in developing countries is generally shorter than the total years spent in formal[43] primary and secondary education *(organisation of education)*. (2) Government spending on education is generally higher in advanced countries *(financial investment in education)*. (3) 'Offshoring' in combination with the 'endogenous skill-biased technological' change brings about differences in (the adoption of) technological advancement across countries, in favor of advanced countries *(demand for education)*. Each of these points is discussed below.

3.3.1. Organisation of education

As follows, I distinguish between two indicators: (1) the official duration of formal primary and secondary education; and (2) the compulsory education age. The former indicates the total years spent in formal primary and secondary education without grade repetition before a diploma of level ISCED-3 can be obtained (short: 'duration'). The latter indicates the minimum age at which one is allowed to leave education, irrespectively of whether the diploma was obtained, or not. In this respect, Anderson (2014) refers to the 'legal dropout age', and this abbreviation will used further in the text.

The indicator 'duration' is a good predictor of the age at which a high school diploma can be obtained, while the indicator 'legal dropout age' highly correlates with the average years of schooling of a population.[44] Both indicators constitute a great part of the organisation of formal education. From UNESCO, I have gathered the latest information on the legal dropout age and the duration of primary and secondary education. These data are presented in Table 2 and Table 3. The difference between 'duration' and 'legal dropout age' indicates, in fact, the total years in post-compulsory education before obtaining a secondary diploma. As such, the years in post-compulsory education are considered

[43] Formal education is generally organized by (government-subsidized) schools and training institutions. It comprises of primary, secondary, and tertiary education.

[44] Based on the data of Table 2 and Table 3, namely the advanced and developing countries together, we estimate a pairwise correlation between compulsory school age and years of schooling of 0.6550 significant at 1 percent level.

voluntarily. For the advanced countries, we estimate a mean difference of +1.79 years voluntary in education and a standard deviation of 1.38, and, for the developing countries, +4.42 years voluntary in education and a standard deviation of 2.14. Taking that the legal dropout age is a compelling argument for students to stay at school (Brunello, Fort and Weber, 2009), school dropout is higher in those countries with many years in post-compulsory education before obtaining a diploma of level ISCED-3.[45]

3.3.2. Financial investment in education

Because of tight(er) budget constraints, total government spending on education is generally lower in low-income countries than in advanced economies; and additional years of subsidized compulsory schooling are costly for the government. For the selection of 49 developing countries (Table 3), it is estimated that a developing country invests about 3.5 percent of GDP in education (source: World Bank[46]). This percentage share of GDP is lower than or can be compared with some developed countries in the year 2007, for example, the United States (5.2 percent) (Source: World Bank[47]), and EU-28 Member States (5.3 percent) (source: Eurostat[48]). Given that per capita GDP is lower in developing countries than in developed countries (see Table 2 and Table 3), it is straightforward to conclude that a budget for education substantially lags behind in low-income countries.

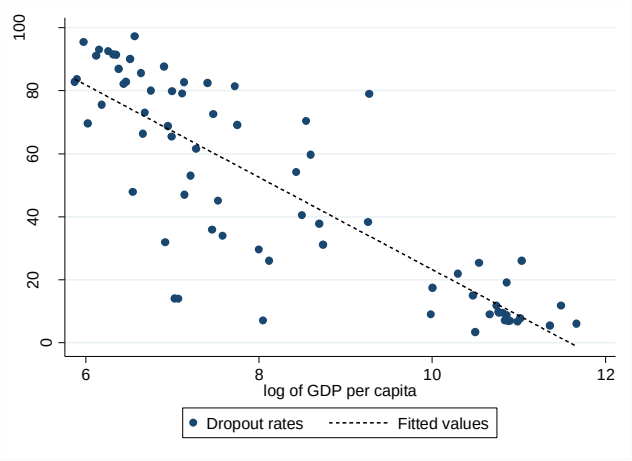
3.3.3. Demand for education

The third explanation deals with the relationship between the school dropout rate and the state of the economy or the level of technological advancement. The latter indicator is often expressed as per capita GDP in the economics literature. Table 2 and Table 3 present statistics on per capita GDP, representative to the years on which the statistics on school dropout are presented (source: World Bank[49]). Next, Figure 1 plots the relationship between the state of the economy (log of per capita GDP, X-axis) and dropout rates (Y-axis) for the full sample of countries (N=73). Log of per capita GDP is used in order to meet underlying assumptions of linearity, and for ease of interpretation. It is observed from the plot that the

[45] Based on the data of Table 2 and Table 3, namely the advanced and developing countries together, we estimate a pairwise correlation between duration and school dropout of 0.7171 significant at 1 percent level.
[46] http://data.worldbank.org/indicator/SE.XPD.TOTL.GD.ZS
[47] http://data.worldbank.org/indicator/SE.XPD.TOTL.GD.ZS?locations=US
[48] http://ec.europa.eu/eurostat/statistics-explained/index.php/File:Main_indicators_for_public_expenditure_on_education_(excluding_early_childhood_educational_development),_2012_ET15.png
[49] http://data.worldbank.org/indicator/NY.GDP.PCAP.CD

state of the economy negatively correlates with dropout rates: the better the state of the economy, the lower the dropout rate.[50]

Figure 15: Plot of state of the economy (log of per capita GDP) and dropout rates for the full sample (N=73; 49 developing countries and 24 advanced countries)



Offshoring and skill-biased technological change[51] can explain what is observed. The demand for low-skilled labour drastically decreased over the past three decades in developed knowledge-based societies owing to technical advancements, while companies moved their labour intensive production to developing countries in order to remain competitive on the international trade market. Berman, Bound and Machin (1997) argue the pervasiveness of skill-biased technological change in advanced countries. As a result, there is great(er) demand for education (skills) in advanced countries (than in developing countries). At the same time, innovations in one country are quickly adopted in other countries, so that labour demand shifts should be observed within the same industries across countries. However, it has been previously argued that technology diffusion goes faster in advanced countries than across developing countries (Fu, Pietrobelli and Soete, 2011).

In conclusion, offshoring and skill-biased technological change lead to two parallel observations. The first one deals with the fact that school dropout rates are higher in developing countries than in advanced countries because there is greater demand for low-skilled labour as a result of labour-intensive production in rather less-developed economies. This provides a disincentive effect among youngsters in developing countries to acquire a high level of education and, consequently, high dropout rates are observed. The second observation deals with the adoption of technologies in developing

[50] The correlation coefficient corresponds to -14.6 percentage points significant at 1 percent level.
[51] Technical advancements and innovations are called skilled-biased, as they are in favor of high-skilled workers.

countries, hereby increasing the demand for high(er)-skilled labour. Therefore, similar to advanced countries, school dropout rates are decreasing over time. These results using DHS-data are available at the author upon request.

4. What determines or 'triggers' school dropout?

Across countries, obtaining a diploma of upper secondary education is by now so important that the dropout is stigmatised as 'failed' (De Witte et al., 2013). However, the definition of school dropout does not reveal why exactly the golden standard, associated with life -time success, is equal to obtaining at least a high school diploma, notably (and preferably) at some point in the young life. The set of criteria used for defining school dropout reveals something about the values attached (by society) to being certified with a secondary diploma, or not. On the one hand, it is believed that *not* being properly certified accurately predicts the risk profile of these youngsters, namely those personal and social characteristics that differentiate school dropouts from graduates (Vizcain, 2005; Henry, Knight and Thornberry, 2012). These characteristics, in fact, refer to the determinants of school dropout. The main advantage, then, of having an indicator for school dropout is that it can be associated with different variables that determine the decision to leave education or training early. This body of knowledge can be particularly relevant for politicians, educators (school principals, teachers and parents), or other stakeholders in education, in order to develop programmes that prevent students from leaving education early. School dropout prevention programmes that aim at tackling the problems leading to early school leaving can give youth at -risk the necessary head start in life (Cabus and De Witte, 2015a). On the other hand, it should also be considered that, from a pedagogic perspective, identifying who is 'at-risk' can also be counterproductive when the risk-status becomes a stigma (De Witte et al., 2013). This is not helping a youngster ahead.

This section presents the determinants of school dropout in detail. Following Rumberger (2001, 2011), at least four sets of school dropout determinants can be distilled from the literature, namely: determinants at (1) student -level; (2) family -level; (3) school -level; and (4) neighbourhood -level. In addition, a new category, the economic determinants of school dropout, is added to the traditional framework, so that we have five sets of determinants in total (Cabus, 2013). Below these five sets of school dropout determinants are discussed using findings from scientific articles published in peer reviewed journals mainly between 2010 and 2016. Rumberger and Rotermund (2012) and De Witte et al. (2013) are literature reviews focusing on literature published before 2010. This earlier literature can

be used below when the insights from these studies are considered necessary to support the story. But before going to the discussion of the selected set of scientific articles below, a caveat is in place. This caveat concerns difficulties with straightforward statistical inference from the evidence that is presented in the articles. These difficulties directly follow from the methodologies used by the authors, and, as such, this section starts with a brief review of methodologies applied in the selected studies before I discuss the studies' contents.

4.1. Methodologies

School dropout has been studied by using various research strategies, for example: ordinary least squares regression techniques or other forms of structural equation modeling (Anger and Heineck, 2010; Altschul, 2011); and (multinomial) logistic regressions or bivariate probit models (McCaffrey et al., 2010; Crowder and South, 2011; Traag and van der Velden, 2011; Henry, Knight and Thornberry, 2012); and aggregate studies (Lavrijsen et al., 2015). These particular studies are mostly aiming at a better understanding of school dropout determinants by estimating correlations rather than identifying the causal effect of a determinant on school dropout. Correlations are not able to isolate the effect of a relevant determinant on outcome variables (like educational attainment and school dropout) because of endogeneity issues, omitted variables and (often negative) selection biases. I assume that this understanding lies at the basis of an observable shift towards evidence-based education research over the past 5 (to 10) years. For example, Anderson (2014) and Cabus (2013) exploit difference-in-differences-in-differences identification strategies; Cabus and De Witte (2015a) combine difference-in-differences with propensity score matching techniques; Price (2012) use the nearest neighbor matching estimator in combination with least squares, tobit and median regression; De Witte and Csillag (2013) construct a quasi-experimental setting for evaluating the differences in outcomes between control schools and treatment schools; Chevalier et al. (2013) identifies instrumental variables; Song (2010) analyses the causal order by using the history of (sequential) events; and Baird et al. (2010) and Chetty, Hendren and Katz (2016) evaluate a randomized intervention. These methodologies have in common that they aim for isolating the effect of one particular determinant on school dropout, while, at the same time, aiming at knowledge-base on the 'true' magnitude and sign of the effect. It is clear that some studies will be more successful in doing this than others. In general, it is acknowledged that studies that are able to exploit exogenous variation in the inspected determinant owing to policy measures or interventions are the best among evidence-based (causal) research. Two examples: Anderson (2014) exploits changes between states and over time in laws on the minimum school dropout

age in order to identify the impact of those changes on juvenile crime arrests (Section 4.2.4). And Chetty, Hendren and Katz (2016) evaluate the Moving to Opportunity Experiment, an intervention that randomly selected low-income families living in (five) US cities (Section 4.5.2).

Notwithstanding that it is important to understand the quality of the research in order to assess the value of the evidence, it appears that, when compared to pre-2010 literature reviews, no particular 'new' dropout determinant is found and discussed in post-2010 studies. However, I do observe that, owing to the shift towards evidence-based education research, new insights are increasingly gained when it comes to 'what works' in the fight against school dropout. In this respect, Rumberger and Rothermund (2012, p.492) wrote: *"Understanding why students drop out of school is the key to designing effective interventions to help solve this critical and costly problem. Yet identifying the causes of dropping out is extremely difficult."*

4.2. Determinants at student -level

The first set of determinants deals with the student himself, and includes factors such as student behaviour and perceptions and student cognitive and non-cognitive capabilities. In the literature, these determinants of school dropout consist of, among others, problem behaviour and disengagement (Fall and Roberts, 2012; Henry, Knight and Thornberry, 2012; Rumberger and Rotermund, 2012); poor prior academic achievement (Traag and van der Velden, 2011; Casillas et al., 2012); lack of intrinsic motivation and high opportunity costs of schooling (Cabus and De Witte, 2016); sexual risk behaviour, teenage pregnancy, and early marriage (Baird et al., 2010); marijuana use (McCaffrey et al., 2010); and juvenile delinquency (Anderson, 2014). These characteristics are then again often associated with age (older students being more likely to drop -out, for example, due to grade repetition), gender (boys drop -out more than girls) and ethnicity (ethnic minority students are more likely to drop -out at school than native students) (Traag and van der Velden, 2011; Legewie and DiPrete, 2012; Cabus, 2013; De Witte et al., 2013).

4.2.1. Student engagement

In the educational literature on school dropout, there is no other topic so heavily discussed than the relationship between student engagement and withdrawal from school. Already in the 1970s, Tinto (1975) and Spady (1970, 1971) were discussing the optimal match between the student and the school in order to stimulate student engagement and, consequently, avoid the process of student attrition. The

participation-identification model (Finn, 1985) further explains that lack of participation in all kind of school activities, or changing school too often, may lead to disengagement and to unauthorised school absenteeism and eventual dropout.

The historical insights into student engagement and identification are still relevant in the fairly recent work of Fall and Roberts (2012). The authors theoretically argue and empirically test multiple, often complex relationships between perceived identification with school (and perceived control) and school engagement; and between school engagement and school dropout. From their model, they indicated that the social context like support from parents, peers and teachers influence and/or mediate school engagement, at the academic- and behavioural -level, and the same factors affect also students' self-perceptions. Low students' self-perceptions, in turn, influence and/or mediate disengagement and with this also school dropout.

Because of the undoubted role of student engagement in the process of withdrawal from school, Henry, Knight and Thornberry (2012) construct the 'school disengagement warning index'. The authors confirm that this index can be used to accurately predict dropout and problem behaviour such as serious delinquency, substance abuse, and official offending. As such, school teachers and principals can better anticipate those students at-risk by using dropout prevention programmes. Unfortunately, Henry, Knight and Thornberry (ibid.) do not explicitly refer to successful interventions once students at-risk are detected by the instrument.

Rumberger and Rotermund (2012) also establish a relationship between student disengagement and poor academic outcomes. They argue that detrimental activities outside school and and deviant behaviours can foster student disengagement, in particular juvenile delinquency, drug and alcohol abuse, teenage parenting and childbearing (p.495), and play an important role in students' decision to stay or leave. But the authors also discuss that there are many reasons why individuals never obtain a secondary diploma in their lives, and it is often a complex interplay between those determinants, often related to background characteristics and experiences of the students, that provide them with the necessary incentives to leave education early.

4.2.2. Prior academic achievement

One such other factor that may lead to early school -leaving is poor prior academic achievement. Overall poor student performance is often associated with indicators as: long truancy spells (Henry, 2007; De Witte and Csillag, 2013); grade repetition (Jimerson, 1999); and being tracked in vocational technical education (Planc, DeLuca and Estacion, 2005; De Witte and Cabus, 2013). These indicators are also mentioned in the literature as contributing to school dropout. According to the present findings of Casillas et al. (2012), prior academic achievement is the strongest predictor of grade point averages and school failure later in the school career. Furthermore, Traag and van der Velden (2011) indicate that cognitive abilities, prior student performance, and motivation determine the (willingness of) future investment of the student in schooling. Clearly, there are some endogeneity issues to address when looking at the relationship between prior academic achievement and school dropout. For example, a student may leave education early because his grade point averages were not enough to pass the high school exit exam (Ou, 2010), or the student may also fail academically because he has not been engaged in the past (Rumberger and Rotermund, 2012). Ou (2010) examines the former causal relationship by looking at students who enrolled in high school in New Jersey between 2002 and 2006. Therefore, he exploits a regression discontinuity design that compares students at the margin of passing-failing the high school exit exam. He finds that students, who barely failed the exit exam, were significantly more likely to leave education early, and compared to those students who barely passed the exit exam.

4.2.3. Motivation

Cabus and De Witte (2016) also mention motivation as an important determinant of the decision to drop -out of school. Based on the theoretical frameworks of Cameron and Heckman (1998) and Keane (2002), the authors answer the question ‘why do students leave education early’. Hereby, the model mainly includes student-level factors, besides aggregate -level factors like state of the economy and policy programmes that aim at reducing school dropout. Among student-level factors, the authors distinguish between intrinsic motivation and extrinsic motivation, where the former denotes the general like or dislike of school and aspirations, and the latter, for example, punishment from parents when the child had an unauthorised absence from school. Note that student motivation is also discussed as a single contributing factor in theoretical models of student (dis)engagement (Fall and Roberts, 2012). Furthermore, in the model of Cabus and De Witte (2016), and in line with Rumberger and Rothermund (2012), an important role is ascribed to extracurricular activities. The authors indicate that school

dropout is associated with the optimal allocation of time (a student decides whether to attend school or join extracurricular activities), and the opportunity costs of schooling (one cannot participate in extracurricular activities while in school). They conclude that students leave education early when the costs, namely the efforts (exerted motivation) and the opportunity costs of schooling, are greater than the benefits of school.

4.2.4. Behavioural factors

Posing risk or deviant behaviour in terms of juvenile delinquency or crime can be disastrous for academic outcomes (Henry, Knight and Thornberry, 2012; Rumberger and Rotermund, 2012). Several authors have investigated whether keeping school going youth in school is effective in reducing risk behaviours and, in turn, boosts graduation. In this respect, Baird et al. (2010) indicate that conditional cash transfer programmes in Malawi not only reduce school dropout, but are also effective for reducing sexual activity, teenage pregnancy and early marriage. McCaffrey et al. (2010) analyze the adverse effects of marijuana use on dropping out. Their findings are similar to previous research on the relationship between educational attainment and Cannabis use (Fergusson, Horwood and Beautrais, 2003); alcohol use (Chatterji, 2006a); or illicit drug use (Chatterji, 2006b). Finally, Anderson (2014) estimates a significant negative effects of the compulsory education age on juvenile delinquency in terms of property and violent crime arrests. The findings of Anderson (ibid.) are particularly interesting for this line of literature, whereas he addresses potential endogeneity issues (mainly, owing to reversed causality) by using a difference-in-differences design (Section 4.1).[52] It is concluded that keeping school going youth in school reduces time and opportunity to commit delinquencies and crimes.

4.3. Determinants at family -level

The second set of determinants deals with the situation at home. Students can leave education too soon because of family reasons (often, beyond control of the child). Indicated are, among others, father's absence (McLanahan, Tach and Schneider, 2013); parental involvement in the education of their children at home (Altschul, 2011; Ariës and Cabus, 2015); parents' educational attainment and intergenerational transmission of education (Chevalier et al., 2013); child poverty and growing up in

[52] Endogeneity issues may arise when it is not clear whether juvenile delinquency *caused* school dropout; or whether school dropout *caused* juvenile delinquency.

poor neighbourhoods (Hopson and Lee, 2011); family structure, family transitions, and nontraditional families (Song, Benin and Glick, 2012).

4.3.1. Parents' educational attainment

It is argued that the likelihood to drop -out of school substantially increases when parents have poor educational attainment, but also that innate ability, birth order, family size and family characteristics play an important role in this intergenerational spillover (Black and Devereux, 2010; Black, Devereux and Salvanes, 2010, 2011). Furthermore, Anger and Heineck (2010) find that the positive relationship between parents' education and the cognitive abilities of their children are not only purely genetic, but also driven by parents' investment in those abilities. These findings are much in line with research on parental involvement in the education of their children (see below). And from Chevalier et al. (2013), it is argued that paternal education influences daughters' decision to drop -out at school. Meanwhile, maternal education does not have a role in the child's decision to remaining in school.

4.3.2. Family structure and family composition

The role of the father in the education of his children is emphasised in the literature review of McLanahan, Tach and Schneider (2013). The authors report that father's absence, for example, due to imprisonment, divorce, or death, negatively impacts their children in terms of increased likelihood of school dropout, reduced child social-emotional well-being, and also poor adult mental health. However, they also argue that the effects of father's absence on child outcomes are partly due to unstable family structures, that is: *"[…] children raised apart from their biological fathers are raised in a multitude of family forms -- single-mother families, cohabitating-parent families, stepparent families, blended families, and multigenerational families"* (p.17). As such, rather than the change in family structure as a result of father's absence, family structure itself becomes an important determinant of school dropout. These arguments are sustained by Song, Benin and Glick (2012), who indicate that school dropout rates are generally higher in nontraditional families. They point out that those children from single-mother families are less likely to drop -out than children from single-father and stepparent families. Furthermore, the authors find that children are more likely to drop -out at secondary education when their parents are divorcing or separating. They do not, however, suffer from their parents starting a new relationship (i.e. marrying, remarrying, or initiating a cohabitating relationship).

4.3.3. Parental involvement

There is a lively debate in the literature on the relationship between parental involvement in the education of their children and children's academic achievement (in a broad sense), as indicated in multiple literature reviews on the topic: Avvisati et al. (2011, 2014); Patall, Harris and Robinson (2008); Wilder (2014); Ariës and Cabus (2015).

Wilder (2014) has conducted a meta-synthesis on the effects of parental involvement on academic achievement and points out the multiple definitions with regard to parental involvement, including, but not limited to: communication between parents and the child on school matters; strategies of involvement in the homework; expectations and aspirations of the parents with respect to their child's level and field of educational attainment; and parental involvement in school activities. Furthermore, she argues that, regardless of the definition, there is a positive correlation between parental involvement and academic success. The author reports the largest positive correlations when parental involvement was defined as expectations and aspirations of the parents, and weakest positive correlations when parental involvement was defined as assistance in the homework of children.

Ariës and Cabus (2015) have reviewed the (mainly correlational) literature on parental involvement in homework and its relationship with academic achievement. They indicate that there are different parental involvement strategies in the homework process, but only direct involvement in assisting children during homework tasks significantly improve academic achievement. The authors point out that meta-strategies should be taught (by the school) to parents in order to facilitate effective direct involvement in the homework task. Lack of knowledge among parents on how to effectively assist the child in homework might explain why Wilder (2014) only found weak positive correlations for this line of research. Furthermore, Cabus and Ariës (2016) find that, in the Netherlands, not only parental involvement in the child's homework, but also communication between parents and the child on school matters, improves test scores. It also reduce grade repetition (a strong predictor of school dropout), in particular when both parents are involved.

Altschul (2011) considers the effectiveness of parental involvement in Mexican American families living in the US, an ethnic group at-risk for poor academic outcomes. The author finds that, among Mexican families, parental involvement in school organisations is less effective than involvement in the home. She also indicates that parents' financial investment in the education of the children has a higher impact on academic performance than forms of parental involvement that require a real time investment.

Another branch of literature discusses why variation of parental involvement between and within households exists, and how this may affect children (Black, Devereux and Salvanes, 2011; Price, 2012). For example, Price (2012) indicates that among children of the same age, first-born children receive 20 to 30 minutes additional quality time each day compared to second-born children. When family size increases, parents choose between investments in quality time and hours of working for generating a household income in order to sustain the bigger family (Becker and Lewis, 1973; Becker and Tomes, 1976). If, as it is, parental involvement is an important determinant of student performance (it is), then younger siblings have, on average, higher probabilities of poor academic achievement than the older siblings (Cabus and Ariës, 2016). Moreover, Björklund, Lindahl and Lindquist (2010) indicate a general negative association between household income and family size. This implies that children in poverty, who already have higher probabilities of leaving education early (Hopson and Lee, 2011), are also more likely to having many siblings.

4.4. Determinants at school -level

The third set of determinants describes how a situation at school, or a school policy, can undermine student performance, enhance truancy behaviour, or even may lead to school dropout. The previous literature indicates several determinants at school -level, including: certain class composition (Mora and Oreopoulos, 2011; Belfi et al., 2012); certain school composition (Legewie and DiPrete, 2012); parental expectations about the quality of instruction (Hill and Torres, 2010); switching schools (Cabus, 2015; Gasper, 2012); truancy reporting (De Witte and Csillag, 2013; Cabus and De Witte, 2015a, 2015b); (lack of) comprehensive school support (Cho et al., 2011; Hallfors et al., 2011); and participation in extra-curricular activities in schools (Shulruf, 2011).

4.4.1. Class and/or school composition

Among pre-2010 studies, it is commonly argued that certain types of class compositions (e.g. in terms of socio-economic composition and/or ethnicity, gender, ability, and teacher-student ratio) can negatively affect student motivation, the interaction between students, and the interaction between the teacher and the students (Jencks and Mayer, 1990; Hattie, 2002; and Rumberger and Palardy, 2005). For example, the risk to dropout decreases (for Blacks) with a higher proportion of native ('White') students in schools (Jencks and Mayer, 1990). Rumberger and Palardy (2005) argue in this respect that the effects of socio-economic composition of schools on academic achievement can be mediated by school policies

and practices (e.g. policies dealing with the amount of homework, the amount of academic courses students should take, school safety, and teacher expectations or beliefs about students' (cap-)abilities). Furthermore, Hattie (2002) indicates small advantages in terms of academic achievement for single-sex classes and smaller classes. However, he also argues that 'what happens in the classroom (p.473)' (cf. instructional quality and educational activities) is more important than classroom organisation.

Fairly recent, Mora and Oreopoulos (2011) have investigated empirically the interaction between students and its influence on school dropout. They conclude that non-reciprocating friends, that is, a students who identifies a classmate as a friend, but that friend does not reciprocate, do not significantly influence students' likelihood to drop -out, or other outcome measures.

Belfi et al. (2012) conducted a systematic literature review in order to explore the relationship between class composition (by gender and ability) on two non-achievement outcomes that are correlated with early school leaving, namely: school well-being and academic self-concept[53]. From their findings, it is argued that, at least for smarter students, ability grouping (tracking) is a good practice in terms of well-being, but not in terms of academic self-concept. Furthermore, the outcomes of school well-being and academic self-concept of the female students are significantly improved in single-sex classes.

Legewie and DiPrete (2012) also focus on the influences of gender composition, but not at the class-level, but at the school-level. The authors have investigated whether and how school context influence the gender gap, namely: boys are more likely than girls to underachieve and drop -out at secondary education. It is argued from empirical evidence that, among boys, anti-school attitudes and behaviour are more easily developed in a school environment that indicates learning as 'feminine' (or as something that only women like to do). School composition by socio-economic status plays an important role in creating this school environment, in the way that it can influence perceptions at school about what is masculine.

Class and/or school composition does not only affect (non-)achievement outcomes while in high school, but it also can influence student post-secondary outcomes. In this respect, Bifulco, Fletcher and Ross (2011) find that, if the share of classmates with college educated mothers increases, then students are

[53] The authors did not define academic self-concept. Byrne (1996) indicates that academic self-concept deals with the ability of a student to assess or evaluate his own capabilities through learning from his past experiences and his environment.

less likely to drop -out and more likely to attend college. The percent share of immigrants in class did not impact upon these post-secondary outcomes.

4.4.2. Switching schools

Transitions from one grade/level/school to the next put students at risk of school dropout, especially when students have to physically switch schools and have to attend classes with different peers and teachers. Transitions, therefore, can lead to student disengagement. Furthermore, Gasper (2012) indicates that switching schools is associated with prior academic achievement. However, controlling for engagement and prior academic achievement in a propensity score matching framework, the author concludes that switching schools remains disadvantageous for leaving education early. This finding indicates that it is not only engagement and prior academic achievement that can explain the decision to drop -out of school after switching schools.

One study has evaluated a school-based intervention aiming at smoothing the transition between the pre-vocational school and the vocational school (Cabus, 2015). This intervention mainly consisted of identifying those students at-risk by improved communication between the pre-vocational school and the vocational school. At the same time, schools received a bonus for every school dropout less compared to the previous year. From the results, it is argued that the intervention failed in the year after implementation, especially for ethnic minority students who faced an increase in the likelihood to drop -out at school. Cabus (ibid.) argues that, most likely, the intervention did not work because schools faced an incentive to keep students at-risk of dropping out away from the schools in order to collect the bonus. Therefore, risk-students were more likely suspended or forced to leave school (early).

4.4.3. Truancy reporting

Unauthorised absence from school, or truancy, has been highlighted in the previous literature as an important trigger for student disengagement and a predecessor of school dropout (Attwood and Croll, 2006; Henry, 2007). Truancy, in fact, is an early signal of school dropout and call for increased care for at-risk students at the school-level (De Witte and Csillag, 2013). However, like school dropout, truancy is best tackled at various levels. Cabus and De Witte (2015) find that truancy reporting (by professional mentors and teachers), in combination with home visits (by social workers and compulsory education

age consultants), are effective in tackling school dropout in the Netherlands. In this way, increased care for truants evolves from targeted-, to comprehensive school support.

4.4.4. Comprehensive school support and extra-curricular activities

Comprehensive school support encompasses a range of policies often found to be useful in developing countries. It includes subsidies to help parents with the payment of school fees, a school uniform, and a person dedicated to visiting children at the home in order to solve problems with school absence or dropout. It is proven to be an effective strategy for improving school attendance in Kenya (Cho et al., 2011) and in Zimbabwe (Hallfors et al., 2011). Both studies indicate that improved school attendance also reduced the risk of HIV infection among orphan girls. As such, there is strong overlap between the school -level determinants in the form of 'truancy policy' and 'comprehensive school support'.

Likewise, the provision of extra-curricular activities in schools can be placed in the broader school context. It is *"an integral component of the school life* (Shulruf, 2010, p.594)*"* and participation rates in the US are very high. The literature review of Shulruf (2010) indicates a positive but small correlation between participation in extra-curricular activities and educational attainment. The author also indicates that there is a general lack of causal studies in this line of research and, therefore, the evidence on the effectiveness of extra-curricular activities is inconclusive.

4.5. Determinants at neighbourhood -level

A fourth set of school dropout determinants deals with the neighbourhood wherein children grow up. These determinants include, but are not limited to: neighbourhood socio-economic characteristics and distress (McBride Murry et al., 2011; Porche et al., 2011; Haelermans and De Witte, 2015); and duration of exposure to disadvantaged neighbourhoods (Wodtke, Harding and Elwert, 2011; Crowder and South, 2011; Chetty, Hendren and Katz, 2016).

4.5.1. Neighbourhood socio-economic characteristics and distress

A substantial body of literature exists on the relationship between neighbourhood socio-economic characteristics and educational attainment (among others, Ensminger et al., 1996; Aaronson, 1998; Vartanian and Gleason, 1999; Crowder and South, 2003). Findings of these studies indicate that the percent share of poor neighbors and the availability of work (and, consequently, the unemployment

rate) in the area increases the likelihood to drop -out of secondary education. This likelihood is highest among ethnic minority groups, but can be diminished by positive characteristics of residents[54] living in the immediate neighbourhoods (Vertanian and Gleason, 1999). It is also argued that neighbourhood distress most heavily affects recent movers into a poor neighbourhood (Crowder and South, 2003; Haelermans and De Witte, 2015).

Why growing up in poor neighbourhoods has such detrimental effects on student success, is not yet clear from previous literature (Ainsworth, 2002). Murry et al. (2011) conducted a literature review on the effects of neighbourhoods on youngsters' development. They suggested that students living in poor neighbourhoods have only few opportunities to cross borders to neighbourhoods that provide access to better education and jobs. Yet, these positive neighbourhoods are necessary to provide school going youth with incentives and role models to stay at school and attain job market aspirations.

4.5.2. Duration of exposure to disadvantaged neighbourhoods

Wodtke, Harding and Elwert (2011) have investigated the duration of exposure to disadvantaged neighbourhoods on the likelihood to drop -out of secondary education. They have analysed the outcomes for 4,154 children from age 1 to 17 for whom data were collected in the Panel Study of Income Dynamics. Findings indicate that growing up in disadvantaged neighbourhoods substantially reduces the likelihood to graduate from high school. The detrimental effects are largest for black children, but are also substantial for nonblack children. Crowder and South (2011) also use data from the Panel Study Income Dynamics. The authors estimate a decreased likelihood of high school graduation when children grow up in poor neighbourhoods. However, the effects of poor neighbourhoods on educational attainment are offset by socio-economic advantage in the surrounding neighbourhoods, and this holds in particular for black Americans. Similar conclusions are reached by Chetty, Hendren and Katz (2016), who have studied the effects of the Moving to Opportunity (MTO) experiment in the US on children's long-term outcomes. In particular, the authors explore the effects of MTO on the education and earnings of those children who moved from poor neighbourhoods to high(er) income areas (also called residential mobility). Young children benefitted from the MTO experiment in terms of increased college attendance and earnings. MTO also reduced the likelihood of children being raised in single parent households. However, high school graduation did not increase for adolescents,

[54] One example for positive characteristics of residents is the percent share of residents having a (good and well-paid) job.

who moved at a later point in their school career than young children. It is argued that moving may have disruptive effects on adolescents, as they might lose their social network as a result of the movement. Therefore, the authors suggested that it is important to move to better environments at a younger age in order to benefit from it in terms of educational attainment and earnings; but also in terms of other child outcomes like health and subjective well-being (Ludwig et al., 2013).

4.6. A fifth category: economic determinants of school dropout

A fifth and final set of school dropout variables deals with 'the economic determinants of school dropout'. This category mainly assesses the connection between education and the labour market and the transition from school -to -work within the scope of school dropout. Within this category of variables, I include individual preferences for work while in school (Allen and Meng, 2010); or the training of students in the firm instead of at the school site (Black et al., 2012). But also the socio-economic context (like poverty rates, youth unemployment rates, and inequality in access to education; De Witte et al., 2013), and system characteristics (matching students to schools or educational levels; van de Werfhorst and Mijs, 2010; Hill and Torres, 2010) and the institutional context (the way a country organises vocational education and training; Lavrijsen and Nicaise, 2015), are included in the set of economic determinants, as they are strong identifiers of 'the system' in which people gain access to education, evolve, learn, and, eventually, become productive individuals on the labour market. Finally, recall that in Section 3.3 I already noted the influence of the state of the economy on dropout rates.

4.6.1. Preferences for work

In the early work of Reich and Young (1975), it is discussed that youngsters leave education early when they prefer work over additional years of schooling. The authors suggested that in the 1970s more than 50 percent of school dropouts actually left education early because they had the opportunity to enter employment. Allen and Meng (2010) have investigated why students left education without a diploma in the Netherlands, and found that work is the second most chosen reason after studying the wrong subjects.

Theory indicates that the opportunity cost of schooling is an important explanation for the (student-level) preference of youngsters for working (Becker, 1962). The opportunity cost of schooling is often expressed in foregone earnings when spending one extra year at school. Each subsequent year (or other

time period) students balance the costs (and efforts) of schooling against the benefits of schooling. Among the benefits of schooling, one can think of increased future earnings and/or fulfilling professional aspirations for which higher educational attainment is necessary. In this respect, Allensworth (2005) argues that students will choose their optimal years of schooling already early in the study curriculum in accordance with their optimal education -job match.

Research by Coleman (1984); Ruhm (1997); and Light (1998, 1999) indicates that students can earn a wage while being at school owing to dual tracks and other forms of school-work combinations most often provided in public or privately organized vocational education and training schools. The labour market then literally penetrates the school environment, so that school-going youth is connected with the job market already at early ages. Black et al. (2012) argue that vocational students are decreasingly likely to drop -out of school when they are offered structured workplace training, and, moreover, are increasingly likely to find jobs on the labour market owing to in -school training programmes. Hanushek et al. (2011) also argue the advantages of in-school training programmes in terms of better employment outcomes in the years after leaving education (early). However, some disadvantageous effects are observed in the long-run, when vocational students are increasingly likely to be unemployed compared to general and academic students.

4.6.2. The opportunity costs of schooling

This coincidence of beneficial short term and deleterious long term impact of in –school training programmes occurs for two reasons. First, in the short-run, vocational students are increasingly likely to leave education (early) in times of economic revival, when there are more jobs available on the labour market in, for example, construction, trade and commerce. When the state of the economy is good, the demand for flexible (and cheap) labour force rises. Vocational students, who are already connected with the labour market, are immediately available, and, moreover, in some cases, the employer also knows the expected productivity of those youngsters owing to experience with employing apprentices at the company. Consequently, employers may 'pull' students out of school, by offering them contracts, in order to anticipate or meet increased firm production in times of economic revival (Cabus and De Witte, 2011).

Second, vocational students pay (higher) opportunity costs of schooling and exert (higher) intrinsic motivation efforts in order to stay at school (than their academic peers) (Cabus and De Witte, 2016).

Furthermore, vocational students are offered higher wages than their academic peers on the labour market right after leaving the secondary educational level early (Cabus and Haelermans (2015)). These aforementioned factors 'push' students out of school.

However, in the long -run, the decision to drop -out of school undermines the competitiveness of vocational students, compared to their academic peers, on the labour market (Hanushek et al., 2011). In line with theories on signaling and screening, this may be owing to the signal they produce to new employers of being unproductive, as they did not obtain a high school diploma (Spence, 1973; Riley, 2001). Or else, in line with the human capital model of Becker (1962), it may be that their academic peers *are* more productive. Finding a new job for school dropouts can, therefore, be more difficult than for graduates. Furthermore, the jobs created in times of economic revival are mostly unstable, because they depend on the economic climate. Thus, once vocational workers lose their jobs, for example, in times of economic downturn, they more easily end in long-term unemployment (Brunello and De Paola, 2014).

4.6.3. Being employed while in school

Besides employment intentionally organised for vocational students in order to learn a profession, adolescents from all types of educational tracks are often engaged in out –of -school employment while still being enrolled in school. McNeal (2010) indicate that work (beyond school time) increases the likelihood to drop -out of school, and this is most prevalent among students from the lowest socio-economic groups, and in local labour market areas with opportunities for future employment.

4.6.4. Socio-economic environment

At country- or regional -level, Lavrijsen and Nicaise (2015) indicate that high(er) poverty rates increase the dropout risk amongst children of poorly educated parents; moreover students from low socio-economic groups are more likely to drop -out when the youth unemployment rate is high. De Witte et al. (2013) conclude that a strong socio-economic environment in terms of economic development, tackling poverty and good integration of newly arrived immigrants, is associated with high completion rates.

4.6.5. System characteristics and institutional context

The composition of classes and schools is not only due to the school choice of parents or children, or the place of residence, but may also be the result of tracking systems that aim at an optimal match between students' competencies and the educational level offered at the school (e.g. academic or pre-university education, general education, and vocational education and training) (for a discussion on the relationship between ability tracking and educational attainment, see also Hattie, 2002). These systems (and variants) are common practice in many parts of the United States and the European Union (van de Werfhorst and Mijs, 2010). It is argued by van de Werfhorst and Mijs (2010) that tracking systems can increase inequality (in terms of academic achievement or opportunity) between different socio-economic groups and between native inhabitants and ethnic minority groups. As pointed out earlier, socio-economic composition of schools can have adverse effects on school dropout (Section 4.4.1). Hill and Torres (2010) confirm this in their study on Latino families. Despite having strong educational values and high aspirations for their children, Latinos have the highest dropout rates in the US. The authors argue that schools do not meet the needs of Latino parents and their children in several ways. Latino students most often attend the most poorly equipped schools and are more likely placed in vocational tracks. These schools do not promote academic success and upward mobility owing to education in the same way as the parents do, hereby undermining student performance and increasing the likelihood to drop -out at school.

5. Conclusion

This chapter has dealt with the question "Why do school dropout rates vary so much across countries?" Definitions and data sources for school dropout regularly differ from country-to-country, and, as a result, it is difficult to find a large international dataset that can be used for cross-country comparisons of school dropout rates across. A database containing information on school dropout status measured in a uniform way, and preferably measured at the level of the individual student, will facilitate international comparisons, and is important for further research on the determinants of- and effective approaches for tackling school dropout. This chapter provides a good example of such database for developing countries. Next, I argue that country-level dropout rates do not reveal who is most at-risk of leaving education or training early. This chapter relies on the framework of Rumberger (2001, 2011) in order to classify the determinants of school dropout retrieved from a post-2010 literature search and in order to discuss who is most at-risk. Furthermore, I add a fifth category, the economic determinants of

school dropout, to the traditional framework. From this elaborated framework two important conclusions can be made: (1) theories of the process of student disengagement cannot fully explain the substantial variation and trends in aggregated-level school dropout rates across countries. If, the problem of school dropout is complex and hard to influence with prevention policy (it is), then increasing enrollment rates in secondary education, as is observed for advanced- and developing economies, should lead to a proportional rise of school dropout rates. Instead, a fairly steady downward sloping trend of the school dropout rate is observed over the past 15 to 25 years for almost all countries. Further research should indicate *why* students are obtaining additional years of schooling in nearly all countries and over time. Hereby, I argue that the economic determinants of school dropout can offer an important point of departure for these studies. And (2), one can rightly question whether the shift towards evidence-based education research has created new insights. Compared to the results from pre-2010 literature reviews (e.g. Rumberger and Rothermund, 2012; De Witte et al., 2013), I can argue that new insights arise mainly on 'what policy measures or interventions work best' for successful school dropout prevention. In fact, policy measures or interventions are expensive, and should only be continued if they have been proven to work. This supports (the request for more) evidence-based education research.

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A Secondary Diploma for All and All for Better Positions on the Labor Market? – On Private and Public Returns to Vocational Education and Training in the Netherlands

Deni Mazrekaj en Sofie Cabus

Abstract

The human capital hypothesis argues that human capital accumulation in terms of additional years of schooling is a necessary condition for access to better labor market positions. This hypothesis is tested for one European Union country, the Netherlands, which recently increased the compulsory education age from 17 to 18 year-olds in 2007. Using the Dutch policy reform as an instrument for (additional years of) schooling, we estimate private- and public returns to education. This paper benefits from unique administrative data of Statistics Netherlands, on all students who are going to school in the Netherlands, and who were born around the eligibility cut-off. Whereas it is acknowledged that students from vocational education and training (VET) are more likely to leave education early, and, as such, VET-participants can benefit the most from an increase in the compulsory education age, we focus the analysis solely on VET-participants. This yields a representative sample of almost 85 thousands of students born in 1990 and 1991. We find that, owing to the compulsory education age change, students from vocational education and training went approximately one school year longer to school. This additional year of schooling did not increase the likelihood on employment (or unemployment) one year after graduation. Likewise, private returns to the additional year of schooling one year after leaving education (early) did not increase annual wages. However, a similar evaluation of the labor market position of school-leaving youth three years after leaving education (with or without a secondary diploma) reveals that additional years in school facilitates employment opportunities. At the same time, people were less likely depended on social assistance and sickness benefits, but increasingly likely on unemployment insurance benefits. This findings suggests that, owing to the history of employment, and, as such, eligibility on unemployment insurance benefits, a group of people 'escapes' other forms of public assistance, but, instead, benefits from the unemployment insurance. Furthermore, three years after leaving education (early), a positive private return to one additional year of schooling is found of about 9.13 percent and an even higher public return in terms of higher fiscal revenues equal to 14.43

percent. However, these positive returns only arise among Dutch native students, albeit Dutch and foreign ethnicity students were both more likely to obtain a diploma after the reform became effective.

Keywords: Return to Education; Instrumental Variables; High School Dropout; Compulsory Schooling; Vocational Education

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The Effectiveness of Professional Career Guidance Tools, A Literature Review

Inne Vandyck en Sofie Cabus

Abstract

The role of work in people's lives is so integral to human functioning that understanding how to make adequate career choices and following positive career pathways is critical for research on the mismatch between education and employment. Meta-analyses show that work is positively related to indices of well-being, whereas underemployment and unemployment are linked to lower levels of well-being. Since the 1990's however, the context of Western countries is characterized by globalization, a growing need for career mobility and flexibility and unpredictable career pathways. Career counseling can then play an important role in terms of individual and social development. Concurrently, a shift in career guidance is established from study choice and vocational guidance in secondary and tertiary education towards a career guidance perspective in all phases of individual's life span. This paper investigates which career guidance programs are effective in stimulating the right career choice and minimizing mismatch between education and employment. A literature review is conducted according to the guidelines of Petticrew & Roberts (2006). The following search engines were used to find the relevant articles: EBSCO host and Google Scholar (first 100 results). Within EBSCO Host all databases are selected, such as ERIC, PsychINFO, Econlit and Business Source Complete. As synonyms of career guidance is searched for career choice, career exploration, career planning, career counseling etc. Additionally to career guidance, also interventions on study choice are searched for, including synonyms as academic counseling and academic planning. Both strands of research career and study guidance are searched for in the combination of intervention, impact or effect. The search was limited to peer-reviewed literature published between 2000 and 2017. The following criteria were used for inclusion: a) the article need to be peer-reviewed, b) the article had to report on an intervention study and c) the article had to report on an experimental study, but pre-post-test designs were also included. Exlusion criteria were a) the article reported on case studies and b) the article reported on a specific targeted population as juvenile delinquents, battered wives or veterans. Of the 37 studies included, a table was created to summarize each study, as Petticrew and Roberts (2006) suggest addressing information about research question, the theory used, the sample, the design, a summary of the results, and factors that influenced the

effectiveness of the intervention. The preliminary results show a small positive effect of most interventions. In most studies, the social cognitive career theory was used to develop the interventions, followed by Hollands theory of vocational choice and development. Other models were life-span models, theories of personality, and existential theory. Of the 37 studies, 4 studies used a descriptive qualitative design, 21 an experimental design and 12 a pre-post design. 27 studies focused on career guidance in the educational system, 8 on job market and 2 interventions could be used in both the educational system as in the reemployment context. Outcomes which were investigated focused more on the soft skills of the career decision-making process, such as self-efficacy, perceived employability, work engagement, career indecision, seeking of career counseling services. Long-term effects on job market, drop-out and mismatch have yet to be established.

Keywords: career guidance; career counseling; vocational guidance; occupational choice

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