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Levelling the playing field? Active labour market policies, educational attainment and unemployment

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Abstract

Purpose – The purpose of this paper is to investigate how active labour market policy (ALMP) training programmes and hiring subsidies increase or decrease differences in the unemployment risk between lesser and higher educated people during an economic downturn. A focus is put on potential job competition dynamics and cumulative (dis)advantages of the lesser and higher educated.

Design/methodology/approach – The paper uses multi-level data. The fifth wave (2010) of the European Social Survey was used and combined with macro-level data on labour market policies of the OECD. The sample consisted of 18,172 observations in 19 countries.

Findings – The results show that higher levels of participation and spending on training policies are related to a smaller difference in the unemployment risks of the educational groups. Higher training policy intensity is associated with a lower unemployment risk for the lesser educated and a higher unemployment risk for the higher educated. This implies that the lesser educated are better able to withstand downward pressure from the higher educated, thereby, reducing downward displacement during an economic downturn. Hiring subsidies do not seem to be associated with the impact of education on unemployment.

Originality/value – The paper adds to the discussion on ALMP training and hiring subsidies that are primarily rooted in the human capital theory and signalling theory. Both theories ignore the social context of labour market behaviour. The job competition theory and cumulative (dis)advantage theory add to these theories by focussing on the relative position of individuals and the characteristics that accompany the social position of the individual.

Keywords Unemployment, Displacement, Active labour market policy, Cumulative (dis)advantage, Job competition, Matthew effect

Paper type Research paper

Introduction

This study aims to explain cross-national variation in the impact of education upon the unemployment risk using an institutional theoretical perspective. Structural changes in the economy weakened the position of the lesser educated, increasing their vulnerability to economic downturns. Researchers argue that labour market opportunities and outcomes of the lesser educated have diminished over recent decades as a result of the transformation of the economy. Under the influence of technological innovation and economic globalisation, the economy transforms from an industrial economy to a knowledge economy (Powell and Snellman, 2004). Due to technological innovation, labour demand shifts from low-skilled labour to high-skilled labour (Katz and Autor, 1999). However, it also seems that new technologies also affect jobs in the middle of the job structure, such as when routine production and clerical tasks are replaced (Autor *et al.*, 2003; Goos and Manning, 2007).

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Consequently, workers that used to work in the middle segment increasingly compete for jobs with workers in the lower segment. Increased economic globalisation also weakens the labour market position of the less educated due to a reallocation of low-skilled jobs to developing countries (Wood, 1995). Demand for flexible labour also increased to efficiently adjust organisations to market fluctuations caused by increased international competition (McCann *et al.*, 2008). As the likelihood of lesser educated people of having a flexible employment contract is higher (Schmid, 2010), economic globalisation is not only associated with a decrease in local demand for low-skilled jobs, but also with a reduced level of job security for the lesser educated.

The weaker labour market position of the lesser educated makes them more vulnerable to the consequences of economic shocks. During the Great Recession of 2008, lesser educated workers were indeed more susceptible to the economic shocks than the higher educated (Verick and Islam, 2010; Vuolo *et al.*, 2016). Having a higher probability of working in sectors most affected by the economic shock (e.g. the construction sector) and having lower job security, partly explains this (Verick and Islam, 2010). Additionally, during economic downturns, the likelihood of the more educated displacing the lesser educated increases, i.e. people with high or middle education who cannot find a job lower their reservation wage and accept jobs under their educational level. Employers tend to raise their educational requirements when economic circumstances worsen. This causes the highly educated to displace the middle educated and so on. Hence, the probability of being pushed out of the labour market increases more for the lowest educated (Klein, 2015). Studies show, however, that the impact of a crisis differs between countries (OECD, 2010; Verick and Islam, 2010) and that changes in the impact of education upon employment probabilities also differ between countries (Bell and Blanchflower, 2010). Hence, national characteristics mediate the severity of education-related risks during an economic downturn. Explanatory factors for variations in risk distributions between countries, besides the structural changes, include institutional factors such as labour market policies (Bennett, 2016) as well as the specific social and cognitive composition of the low educated in a given country (Gesthuizen *et al.*, 2011; Abrassart, 2013).

Against this background, active labour market policies (ALMPs) are of special interest. These policies intend to improve the labour market position of disadvantaged social groups (Martin and Grubb, 2001). ALMPs try to reduce unemployment by improving the quality of the supply side through upskilling and by reducing hiring risks associated with disadvantaged social groups on the demand side. Both strategies are rooted in the human capital theory and signalling theory. Based on the human capital theory, unemployment is understood to be the product of possessing unmarketable skills (Becker, 1962). Thus, learning skills demanded by employers is necessary in order to improve one's labour market position. Furthermore, hiring decisions are associated with high risks for employers due to information asymmetry regarding the productive potential of applicants. According to signalling theory, employers rely on crude signals as screening devices to reduce the risk of making a costly hiring mistake (Stiglitz, 1975). The educational level of the applicant is one such signal (Arrow, 1973). Along with stating the knowledge and skills of the applicant, educational attainment also signals a level of readiness and an ability to acquire new job-specific knowledge and skills. The latter point is a key, according to Spence (1973), since most relevant skills and specialised knowledge are most likely acquired on the job. Therefore, ALMP programmes that improve the signal of their unemployed participants and reduce their perceived training costs should result in improved labour market opportunities.

However, the empirical results on the market opportunities (increasing options for high-quality jobs and re-employment of unemployed) are mixed (Brown and Koettl, 2015). While the human capital theory and signalling theory lead to compelling insights for critically evaluating ALMPs, neither seems able to account for variations in the observed effects of ALMPs. To better understand the effects of ALMPs, it is important to first differentiate between various ALMP instruments, as their effects differ (Sianesi, 2008). ALMP measures directly linked to improving human capital and reducing information asymmetry include training programmes and hiring subsidies. Training programmes aim at improving the human capital of participants by teaching them skills that are currently in need. In the case of workplace training, a training programme also reduces information asymmetry by providing an opportunity for the employer to acquire information on the participant (Carling and Richardson, 2004). Hiring subsidies are financial incentives that are specifically targeted at hiring the unemployed. Although hiring subsidies resemble wage subsidies, they are different because they are usually of short term, while wage subsidies can last as long as that person remains employed. Furthermore, hiring subsidies are mainly aimed at disadvantaged unemployed, while wage subsidies also cover the employed (Brown and Koettl, 2015). However, in both cases, effects are also observed that undermine the original policy goals. For example, participation in ALMP programmes might also lengthen the unemployment duration, which further hurts a person's chance at employment (van Ours, 2004), displace other workers from their jobs (Calmfors *et al.*, 2001) or be used by social groups that are not the intended target social group (Kocór and Worek, 2017). Any one of these processes can have the net effect of increasing inequality, so more insight into the effects of ALMPs are needed for policy makers to make informed investment decisions.

To investigate the effects of training programmes and hiring subsidies on the variation in the unemployment risk depending on education, the job competition theory and cumulative (dis)advantage theory are used. Neither theory denies the central ideas posited in human capital theory and signalling theory but each provides additional insights. In order to investigate the theoretical expectations following from both theories, a comparative dataset was constructed that links national-level ALMPs to the unemployment risk on the individual level. We use data from the European Social Survey (ESS) of 2010 as it contains data that are collected during the economic crisis and combined the ESS data set with macro-level indicators from the OECD.

This papwe is structured as follows. In the next section, the possible outcomes that training programmes and hiring subsidies might produce are theorised using the job competition theory and cumulative (dis)advantage theory. Then, the data and methods used to empirically test the hypotheses are described. In the following section, the results of my analysis are presented. The paper ends with a discussion and conclusion based on the obtained results.

Job competition and substitution

According to the job competition theory, as explained by Thurow (1975), one's labour market opportunities are always relative to those of others. Employers rank applicants based on the costs they need to reach the full productive potential of a given job, forming a labour queue. This labour queue is matched with the job queue, which is the ordering of available jobs ordered according to their training requirements and rewards. The jobs with the highest training requirements are matched with persons with the lowest training costs until all job openings are filled. Hence, job competition is based on the ability to signal the lowest possible training costs to the employer relative to other applicants. Because the position in the labour queue is always relative, the probability of acquiring a job depends on the strength of the signal compared to that of others . In this context, the level of education is used as a signal for cognitive and non-cognitive skills of the applicant (Parsons, 1959). Non-cognitive skills refer to habits and traits, such as discipline, politeness and attendance, while cognitive skills refer to abilities related to reading, writing and mathematics among others (Farkas, 2003). Research shows that especially in the interactive service economy non-cognitive skills are more highly valued by employers than cognitive skills. However, non-cognitive skills are an additional requirement to cognitive skills, not a substitution (Mýtna Kureková *et al.*, 2016). The options to measure both skill groups during the hiring process differ. Whereas cognitive skills can be more easily measured with standardized tests, non-cognitive skills are harder to measure, which induces the use of subjective criteria (Kmec, 2006). This suggests that when it comes to non-cognitive skills, employers rely more on presumed (stereotypical) group characteristics to order their applicants during the screening process instead of their actual skill level. Following the logic of the job competition theory, the labour queue position of the lesser educated can be improved by ALMPs that reduce training costs and provide opportunities for employers to obtain information on the actual skills and skill levels. However, at the same time, the higher educated would then obtain a lower position in the labour queue, lowering their chances of obtaining a job. As a result, downward substitution should happen to a lesser extent in labour markets that make more use of ALMPs.

Following the theoretical logic of the job competition theory, it is expected that both training programmes and hiring subsidies affect the unemployment risk by influencing the expected training costs and availability of information on the actual skill level of an applicant. Because training programmes are primarily aimed at skill development through general, vocational or firm-specific education (Brunetti and Corsini, 2017), the perceived training costs for employers should be lower. Additionally, educational activities also socialise people for work (Bowles and Gintis, 2000, 2002). Conversely, being outside of the educational system and the labour market implies that a work-related de-socialisation takes place. These signals represent not only higher training costs to employers, but also a lack or loss of attractive behavioural traits. Through participating in training programmes, the lesser educated may correct this and signal lower training costs to the employer based on the possession of desired skills and behavioural traits. Furthermore, it might be expected that participation in ALMP training activities signals a readiness to learn; however, it is also argued that participation in ALMP programmes might stigmatise participants. Research (Bonoli and Hinrichs, 2012) shows that participation in labour market programmes is viewed as a positive signal by employers or is seen as at least better than inactivity during a period of unemployment. The signalling effect of ALMP programme participation tends to differ depending on the distance one has to the labour market. Whereas participation is viewed as a positive signal for those with a weak position, it may have no effect or even a negative effect on stronger participants (Liechti *et al.*, 2017). This suggests that training programme participation mainly benefits the people with less education in terms of improving one's position in the labour queue. Furthermore, when training programmes take place in the workplace, instead of a classroom, these programmes can be used by employers as screening devices to obtain more information on the actual skill level of participants (Brunetti and Corsini, 2017). This potentially reduces the negative consequences associated with assumed stereotypical group characteristics. As these types of programmes are primarily aimed at the lesser educated, they offer them an advantage over the higher educated regarding information asymmetry. Hence, we hypothesise that:

H1. During an economic downturn, the lesser educated have a lower unemployment risk in labour markets with high training programme intensity compared to the lesser educated in a labour market with low training programme intensity, and vice versa for the higher educated.

Hiring subsidies also have the potential to influence labour queue dynamics. In those programmes, the labour costs of participants are (partially) covered through financial measures for a fixed period. Thus, building on the job competition theoretical logic, the training costs to a potential employer are lower and therefore the position in the labour queue of those who are eligible is higher. Consequently, those who are not eligible are pushed to a lower position in the labour queue, reducing their employment opportunities. Furthermore, when participants are employed during a subsidy period, the employer is able to obtain information on the productive potential of the subsidised worker (Brown and Koettl, 2015). Employers may be more willing to retain lesser-educated participants as it potentially reduces negative biases towards these types of workers. Besides reducing information asymmetry, participants also obtain firm-specific human capital (Sianesi, 2008), which reduces training costs substantially. However, it also argued that hiring subsidies have the potential to displace employed workers. Two effects can be hypothesised relating to job competition. First, employed workers are fired and replaced by subsidised workers. Second, in order for employers to become eligible for a hiring subsidy, the educational requirements are lowered and workers are replaced with subsidised workers who are lesser educated (Brown and Koettl, 2015). If these substitution effects would occur, it is more probable that the middle and highly educated are affected in a negative sense. Both educational groups have a higher chance of being employed during an economic downturn than the less educated (Klein, 2015). This implies that:

H2. During an economic downturn the lesser educated in a labour market with a higher hiring subsidy intensity have a lower risk of becoming unemployed than the lesser educated in labour markets with a lower hiring subsidy intensity, and vice versa for the higher educated during an economic downturn.

Cumulative (dis)advantage and the Matthew effect

The possibility also exists that ALMPs increase labour market inequalities between lesser and higher educated people. ALMPs might produce a Matthew effect due to cumulative advantages of higher educated people and cumulative disadvantages of the lesser educated. The central idea of such an effect is that a group-based advantage or disadvantage will grow over time, widening inequality between social groups. Small disadvantages at a certain point in time might prevent closing the inequality gap or make it more difficult to do so. Conversely, small advantages at a certain time point might provide the opportunity to widen the gap even further between groups (DiPrete and Eirich, 2006). In short, cumulative (dis)advantage is a micro-level process that produces a macro-level effect of increasing inequality, i.e. a Matthew effect (Bask and Bask, 2015).

In the process of maximising the output of ALMP programmes during an economic recession, higher educated job seekers might be more favourable than lesser educated candidates. The practice of placing the unemployed with the highest re-employment probability in ALMP programmes instead of those who need it the most is called "creaming" (Brown and Koettl, 2015). It is logical to assume that creaming is more likely to happen during an economic downturn because it increases the probability of budget cuts and to the existence of vacancies that are harder to fill. Even during an economic downturn, the possibility still exists that employers have vacancies that are hard to fill, even though labour supply is relatively high (Erken *et al.*, 2015). If ALMP measures such as training programmes and hiring subsidies are used to reduce mismatching, it is expected that the more educated have a higher probability to obtain employment compared to the lesser educated. Furthermore, not all occupations have the same level of accessibility. Institutions can be used to "artificially" reduce supply for certain occupational groups. In this way, members of those occupational groups are better protected from competition and their position is strengthened. Access to certain occupations can be limited through things like licensing, credentialing and certifying (Weeden, 2002). As people with higher education have generally enjoyed more education, it is expected that the training costs of higher educated people to obtain the desired skills or to get access to the job are lower than those of the lesser educated if they compete for the same job. Thus, this suggests that fewer activation measures or measures enacted at a lesser intensity would be needed for higher educated people to become eligible for the same vacancy compared to lesser educated people.

The higher educated are also more positively predisposed to training and learning activities than the lesser educated. The lesser educated often refer to negative experiences during their educational career as reasons for their not participating in training programmes (Illeris, 2006). Additionally, research shows that a lower willingness to train by the less educated is driven by differing economic preferences and personality traits on average compared to the higher educated, such as the preference for leisure, openness to experience or one's internal locus of control (Fouarge *et al.*, 2013). When people who have a lower willingness to train are forced to participate in a training programme, they often develop coping strategies that hinder the formation of human capital. These strategies involve things like focussing only on what might be personally useful, getting through by making things as easy as possible (instrumentalism) and becoming passive aggressive (Illeris, 2003). All of this suggests that processes of cumulative advantage and disadvantage increase inequality in labour markets with higher levels of training programme intensity. Due to having higher amounts of human capital and lower costs to successfully reintegrate into the labour market, higher educated people are more likely to utilise training programmes successfully. Lesser educated people, on the other hand, are on average more negatively predisposed to training, which hinders their participation and hinders them from successfully obtaining marketable skills. Hence, we expect that:

H3. During an economic downturn the difference in the unemployment risk between the low and the higher educated is greater in labour markets with a high training programme intensity than in labour markets with a low training programme intensity during an economic downturn.

Related to hiring subsidies, stigmatisation is a frequently mentioned cumulative process of disadvantage. It is argued that when hiring subsidies are too narrowly targeted, eligibility signals low productivity. This signal reduces hiring probability and thus increases the unemployment duration (Brown and Koettl, 2015). Because long unemployment spells are also perceived as signals for low productivity (Bonoli and Hinrichs, 2012), hiring subsidies might further weaken the position of the lesser educated who are more likely to become eligible for a hiring subsidy. However, during an economic downturn, the negative signalling function of unemployment and activation programme eligibility should be much weaker. When unemployment is high, individual unemployment is perceived as more normal and, therefore, does not necessarily imply a low quality of worker (Lupi and Ordine, 2002). This implies that stigmatisation based on hiring subsidy eligibility is less likely to happen during an economic downturn. However, if unemployment is widespread, the probability for the higher educated to become eligible for hiring subsidies also increases, especially when eligibility criteria are based primarily on unemployment duration. A potential consequence here is that employers would use hiring subsidies to hire workers who are higher educated. Thus, if hiring subsidies produce a Matthew effect, it is more likely to be a cumulative advantage for the higher educated. As a result, we expect that:

H4. During an economic downturn the difference in the unemployment risk between the low and higher educated is greater in labour markets with a high spending level on hiring subsidies than in labour markets with a low spending level during an economic downturn.

Data and method

To answer the research question, we used the fifth wave of the ESS (2010). The ESS contains micro-level data on 27 countries and includes a total of 52,458 observations. As we are interested in the labour market population, data on individuals younger than 15 and older than 65 are excluded. The micro-level data of the ESS are combined with macro-level data on ALMPs from the OECD because it is expected that the institutional structure of a national labour market partly influences the unemployment risk on the micro-level. The combination of micro-level and macro-level into one dataset allows us to simultaneously model the contextual and individual level variables, which prevents misleading conclusions to be drawn based on aggregated (ecological fallacy) or disaggregated data (atomistic fallacy). A disadvantage of multilevel data is that within-group errors tend to correlate due to common history, which results in standard errors that are too small (Hox, 2010). Several statistical techniques were used to address statistical issues concerning multilevel data. After excluding observations that did not meet the selection criterion and because not all countries in the ESS data set are covered by the OECD concerning specific ALMPs, the analyses were performed on data from 19 countries and 18,172 observations.

Micro-level variables

To measure labour market status, respondents were asked to indicate the activities that they had been doing over the last seven days. If they marked more than one activity, they were asked to mark the activity that best describes their situation. The options included in the analysis were paid work, unemployed and looking for a job, and unemployed and not looking for a job. All other options were excluded from the analyses. Because ALMPs primarily aim to transition both the unemployed who are looking and not looking for work into employment and aim to prevent the employed from transitioning into unemployment, the analyses mainly focus on the difference between employment and unemployment in general. Both unemployment categories were therefore combined to form one unemployment indicator.

Although the theoretical section implies a certain dichotomy, a continuous variable was used because both groups refer to the tails of the educational distribution and theoretical reasoning is linear. Furthermore, a categorical variable would also increase measurement error by grouping people in relatively broad categories. Therefore, the educational level was measured using the International Standard Level of Education (ISLED) scale. The educational classifications from the International Standard Classification of Education (ISCED) are scaled using a cause-and-effect scaling technique and projected on a 0–100 metric using the length of educational career (in years) as a calibration measure. Measurement quality of ISLED outperforms both duration and ISCED as education measures (for a detailed description and testing of ISLED, see Schröder, 2014; Schröder and Ganzeboom, 2014). Because this variable is used in an interaction, it is mean centred.

Due to educational expansion during the last decades, the number of highly educated increased, and consequently, in many European countries highly educated people tend to be younger on average. Hence, age is controlled for and measured in years. On average, people belonging to ethnic minorities also tend to have lower educational credentials and a higher risk of being unemployed. A dummy variable was included to measure if the respondent belongs to an ethnic minority within the country the person lives in. Gender was included as a dummy variable referring to female respondents. A categorical variable measuring trade union membership was also included in the analyses. Trade union membership is negatively related to the educational level and also potentially negatively related to unemployment due to increased labour market protection. Additionally, it is expected that trade union members have more information on ALMPs than non-members due to the information function that the trade union fulfils for its members. This might increase participation in ALMPs among trade union members. The variable consists of three categories, namely: “yes, currently”, “yes, previously” and “no”.

Macro-level variables

The theoretical expectation is that training programmes and hiring subsidies moderate the relationship between education and unemployment. The common practice is to measure ALMP intensity on the national level as a percentage of GDP. However, the OECD also provides an option that operationalises ALMP intensity as the number of participants as the percentage of the total labour force. Both measures are used to check the sensitivity of the observed patterns. A distinction is also made between classroom training and workplace training because the theory suggests that the effects might differ between both forms. A training programme where participants spend 75 per cent or more of the training time in an educational institution is considered to be classroom training. The OECD also provides indicators for training programmes where 50 per cent or where 75 per cent or more of training time is spent in the workplace, both of which are considered to be workplace training. Workplace training also includes apprenticeship programmes that consist of incentives to recruit apprentices or training allowances for disadvantaged groups. Apprenticeships that follow from participation in the regular educational system are not included. Because the intended effects of training programmes generally become manifest in the longer term (Strandh and Nordlund, 2008), e.g. within one to three years (Lechner *et al.*, 2007), we lagged training variables by two years and use measurements from 2008. Moreover, hiring subsidies consist of measures that promote the creation or take-up of new jobs or that promote the improvement of employability through work experience and are paid only for a limited period of time. As hiring subsidies have an immediate effect when they are utilised (Strandh and Nordlund, 2008), measurements originate from 2010. Because these variables are used in an interaction, they are mean centred (Table I).

Method

Because the dependent variable is dichotomous, binary logistic regression is the appropriate analytical method for the analyses. Because the data are clustered (people are clustered in countries), the independence of observations assumption is violated. If the clustering is not

	N	Mean	SD	Min.	Max.
Micro-data					
Unemployment	18,172	0.130		0	1
Education (ISLED)	18,172	50.989	19.694	17.530	91.530
Ethnic minority	18,172	0.055		0	1
Female	18,172	0.519		0	1
Age	18,172	41.581	11.540	16	64
Trade union membership					
Yes, currently	18,172	0.261		0	1
Yes, previously	18,172	0.136		0	1
No	18,172	0.603		0	1
Macro-data					
ALMP training (participation)	19	0.981	0.750	0.040	2.240
ALMP training (spending)	19	0.144	0.112	0.010	0.350
ALMP classroom training (participation)	19	0.632	0.551	0.040	1.970
ALMP classroom training (spending)	19	0.098	0.093	0.010	0.320
ALMP workplace training (participation)	19	0.335	0.380	0.000	1.310
ALMP workplace training (spending)	19	0.038	0.037	0.000	0.100
Hiring subsidy (participation)	19	1.287	1.064	0.070	4.530
Hiring subsidy (spending)	19	0.124	0.113	0.020	0.500

Sources: ESS 2010 (micro-data) and OECD (macro-data), own elaboration

Table I.
Descriptives

accounted for, unreliable estimates are obtained. To correct for this data structure, multilevel analysis is commonly used. Multilevel analysis corrects clustered data by including random effects, which capture the variation between clusters. Fixed effects are also estimated, which are the general relationships between the dependent and independent variables regardless of cluster membership (Hox, 2010).

However, these models are criticised in light of cross-national research. First, the samples of countries used are considered small (less than 25). The low number of countries affects coefficient estimation procedures, resulting in standard errors that are too narrow. As a result, the *p*-values are too small (Bryan and Jenkins, 2016; McNeish, 2016). When using multilevel logistic regression, Bryan and Jenkins (2016) recommend at least 30 countries as the absolute minimum in order to obtain consistent estimates. Hence, the use of multilevel models is less than optimal. However, McNeish (2016) shows in a simulation study that using penalized quasi-likelihood with a Kenward–Roger correction produces trustworthy results. The Kenward–Roger correction is a post-estimation technique that inflates standard errors and adjusts degrees of freedom based on variability within the variable. This produces *p*-values that are more conservative (McNeish, 2017). As SAS is the only statistical programme that offers the Kenward–Roger correction in combination with multilevel logistic analysis, we used the glimmix procedure with the Newton–Raphson with the Ridging optimizer.

Second, because relatively few countries are available in comparative data sets, few control variables on the country level can be included in the model. Hence, multilevel analysis in cross-national research is prone to omitted variable bias (Möhring, 2012). An alternative to multilevel analysis is fixed effect models (FEMs) (Huang, 2016). In FEMs, for comparative cross-sectional analysis, $N-1$ country dummies are included to control for all country-level heterogeneity. Omitted variable bias on the country level is ruled out, and thus, time-specific cyclical components of unemployment as well as the structural components of unemployment are controlled for. However, this also means that main country effects on individual outcomes cannot be estimated (Möhring, 2012). Nevertheless, cross-level interactions can still be included into FEMs because these coefficients also vary on the individual level (Allison, 2009; McNeish and Stapleton, 2016). FEMs were estimated that included interactions between ALMP indicators and the education indicator. Because the main effect of the ALMP variables cannot be included with FEM, the interpretation of the interaction coefficient is more difficult. Therefore, we use the FEM mainly to check the robustness of the interaction coefficients of the multilevel models.

Third, the selection of countries is not random. Thus, influential cases on the country level can have strong effects on the estimates. To investigate the effects of influential cases in the context of ML, Bowers and Drake (2005) advise the use of visualisation techniques to provide additional information on the micro-level relationships within macro-level units. Hence, the within-country effects are estimated while being controlled for the before-mentioned micro-level characteristics and plotted against a country characteristic to visually inspect if the estimates become more positive or more negative when the characteristic specific ALMP programme intensity increases.

To address the methodological issues of cross-national research, we use multilevel analysis, FEMs and the visual procedure side by side to evaluate the relationships found. The multilevel coefficients are used to predict the average labour market status probability if all the analyses indicate that there is a significant and robust interaction. The predicted probabilities are then plotted to ease the interpretation of the interactions.

Results

The results for ALMP training programmes (*H1* and *H3*) are first discussed, which is followed by a discussion on the results for hiring subsidies (*H2* and *H4*). The results of the multilevel logistic regression using participation rates as indicators for ALMP intensity are presented in Table II. The results with the indicators based on spending as a percentage of GDP are presented in Table AI. To test the hypotheses that the difference in the impact of education upon unemployment is smaller (*H1*) or bigger (*H3*) in labour markets with a high intensity of ALMP training compared with labour markets with a low intensity, interaction terms were estimated using both training programme indicators and the indicator for educational attainment. The first model in Table II shows a significant positive interaction between overall training participation and education on being unemployed ($b = 0.011$, $p < 0.05$). A similar pattern is observed in Table AI concerning overall training participation ($b = 0.071$, $p < 0.05$). The FEMs confirm these observations (see Table AII). The plots of within-country estimates of education on unemployment and spending on and participation in overall training both show a general positive relationship (see Figure A1). This suggests that the obtained results are robust against outliers and omitted variable bias on the country level. Figure 1 shows the marginal effects of the interaction between ALMP training participation, based on the multilevel model, that the predicted unemployment risk for the lesser educated is on average lower in countries with a higher participation rate, whereas the unemployment risk is on average higher for people with a higher education compared to a country with a low participation rate. The same pattern is observed concerning training programme spending.

Furthermore, a distinction was also made between ALMP classroom training and ALMP workplace training. Both ALMP classroom training spending and participation positively moderate the relation between education and unemployment ($b = 0.076$, $p < 0.05$ and $b = 0.012$, $p < 0.05$). The results of the FEM (see Table AII) and the plot of the within-country estimates of education on unemployment (see Figure A2) indicate that this finding is robust against outliers or omitted variable bias on the country level. Figure 2 shows that, just like in the case of overall spending on ALMP training, lesser educated people in countries with high participation levels on ALMP classroom training have on average a lower unemployment risk compared to lesser educated people in countries with low spending levels. The opposite holds for people who are highly educated. Tables II and AI also show that the interaction between ALMP workplace training participation and spending does not moderate the relation between education and unemployment. To conclude, the findings support *H1* in the case of overall ALMP training and ALMP classroom training, while *H3* is rejected. In the case of ALMP workplace training, both *H1* and *H3* are rejected.

To test the hypotheses that the impact of education on unemployment is smaller (*H2*) or bigger (*H4*) in labour markets with a high intensity of hiring subsidies compared with labour markets with a low intensity. Tables II and AI show that all the estimates for the interaction effects including hiring subsidies are not significantly different from zero. The FEM shows similar results (see Table AII). After a visual inspection of the within-country coefficients, the same conclusion is reached in line with the numerical analyses. As a result, we conclude that hiring subsidy intensity is not related to the impact of education on unemployment and both *H2* and *H4* are rejected.

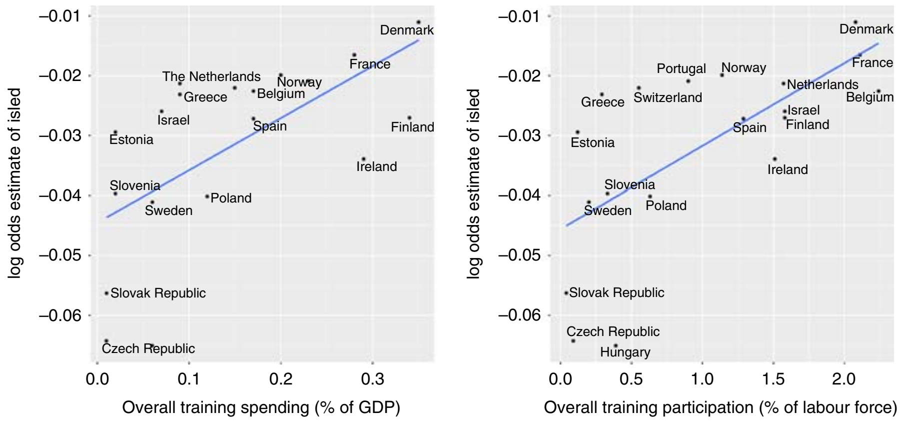
Conclusion and discussion

The study utilises the job competition theory and cumulative (dis)advantage theory, as a contrast to the human capital and signalling theory, to formulate hypotheses about the potential effects that both ALMP programmes have on the impact of education on the unemployment risk. This study finds that hiring subsidy intensity is not associated with the relation between education and unemployment during an economic downturn. Nonetheless, training programmes do seem to affect the impact education has upon unemployment. Besides studying training programme spending and participation in general, a distinction was made between classroom training and workplace training.

Table II. Multilevel logistic regression with Kenward–Roger correction on unemployment as dependent variable (ALMP participation indicators)

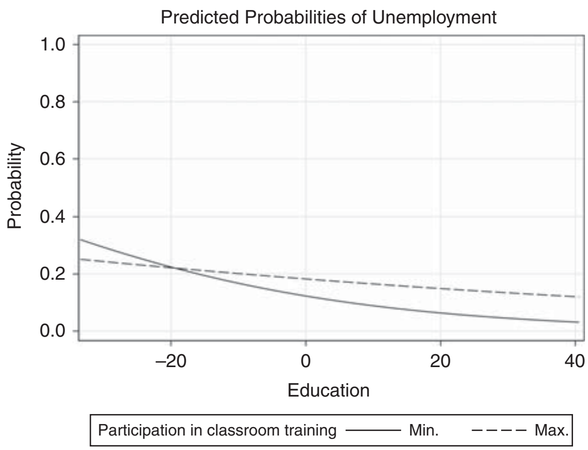
	Model 1			Model 2			Model 2			Model 4		
	Estimate	SE	OR	Estimate	SE	OR	Estimate	SE	OR	Estimate	SE	OR
Intercept	−3.246***	(0.148)		−3.248***	(0.148)		−3.237***	(0.151)		−3.240**	(0.149)	
Education_c	−0.029***	(0.003)	0.971	−0.029***	(0.003)	0.971	−0.029***	(0.003)	0.972	−0.029**	(0.003)	0.972
Training_c (part)	0.186	(0.175)	1.204									
$\text{Education}_c \times \text{Training}_c$ (part)	0.011*	(0.004)	1.011									
Classroom_c (part)				0.242	(0.239)	1.274						
$\text{Education}_c \times \text{Classroom}_c$ (part)				0.012*	(0.005)	1.013						
Workplace_c (part)							−0.043	(0.355)	0.958			
$\text{Education}_c \times \text{Workplace}_c$ (part)							0.015	(0.008)	1.015			
Hiring subsidy_c (part)										0.107	(0.123)	1.113
$\text{Education}_c \times$ Hiring subsidy_c (part)										0.001	(0.003)	1.001
Ethnic minority	0.385***	(0.093)	1.470	0.386***	(0.093)	1.471	0.387***	(0.093)	1.472	0.388***	(0.093)	1.474
Female	−0.133**	(0.047)	0.875	−0.133**	(0.047)	0.876	−0.133**	(0.047)	0.876	−0.132**	(0.047)	0.876
Age_c	−0.019***	(0.002)	0.982	−0.019***	(0.002)	0.981	−0.019***	(0.002)	0.982	−0.019***	(0.002)	0.982
Age_c^2	0.002***	(0.000)	1.002	0.002***	(0.000)	1.002	0.002***	(0.000)	1.002	0.002***	(0.000)	1.002
Trade union membership (ref: yes, currently)												
Yes, previously	1.168***	(0.096)	3.215	1.168***	(0.096)	3.215	1.163***	(0.096)	3.198	1.164***	(0.096)	3.201
No	0.968***	(0.083)	2.632	0.968***	(0.083)	2.633	0.964***	(0.083)	2.622	0.965***	(0.083)	2.624
Variance												
Intercept	0.296			0.295			0.310			0.297		
Education_c	0.000			0.000			0.000			0.000		
N	18,172			18,172			18,172			18,172		
Groups	19			19			19			19		

Notes: $*p < 0.05$; $**p < 0.01$; $***p < 0.001$
Sources: ESS 2010 and OECD, own elaboration



Sources: ESS 2010 (micro-data) and OECD (macro-data), own elaboration

Figure 1.
Within-country log odds estimates of unemployment predicted by education plotted against ALMP training participation and spending



Sources: ESS 2010 (micro-data) and OECD (macro-data), own elaboration

Figure 2.
Predicted probabilities of unemployment based on education by participation in ALMP classroom training

Higher levels of overall ALMP training programme intensity seem to be related to an improved labour market position of lesser educated people and a weaker labour market position of people who are highly educated. The results support job competition theory, which states that the strength of labour market signals is always relative to those of others. Thus, when the employment probability of one increases through a strengthening of the labour signal as the result of human capital development, those of others decrease. This implies that downward substitution is reduced, and the unemployment risk is distributed more evenly across educational groups. The higher educated are less likely to obtain a job with lower qualification requirements because of the stronger position of the lesser educated. Other researchers present similar findings. For instance, Bennett (2016) shows that with stricter employment protection legislation the less educated have a lower probability of becoming unemployed, while, at the same time, stricter EPL is associated with a higher unemployment risk for the highly educated.

Furthermore, no support was found that cumulative advantages associated with the higher educated decreased their unemployment risk further or that cumulative disadvantages of the lesser educated increased their unemployment risk. Micro-level processes such as creaming practices, the more positive predisposition to learning by the higher educated, the negative effects of mandatory participation or the increased probability of activation programme eligibility by the higher educated do not seem to result in a Matthew effect on the macro-level. However, as this study only investigates training programmes and hiring subsidies, it might be possible that other programmes induce a Matthew effect. Nonetheless, the results indicate that human capital theory is somewhat limited in its explanatory power concerning the relation between education and unemployment. Although its core premise that upskilling leads to a stronger labour market position seems to hold, this mechanism operates in a social context and therefore affects others also.

Policy makers should be aware that non-participants can also be affected by policy interventions and improving the labour market position of one group might deteriorate to position of another group. Thus, training programmes can be used to strengthen the position of people with less education during an economic downturn but, at the same time, these programmes seem to increase unemployment among people with higher education. This might be somewhat problematic in labour markets that focus more heavily on knowledge production due to negative consequences of unemployment, such as skill deterioration. This might hamper economic productivity due to reduced labour supply when the economy starts to recover.

This study is not without limitations. Implicit assumptions were made in the theoretical section that the unemployed individuals with varying educational backgrounds actually use the ALMP programmes available to them. However, data on individual utilisation of ALMP programmes are not included in the analytical framework. Thus, we do not know how higher ALMP intensity on the national level influences the use of ALMP programmes on the individual level. Future research should focus on how the configuration of the ALMPs might affect the way ALMP programmes are used by the lesser and higher educated. Furthermore, the indicators used to provide a measurement of ALMP intensity on the national level are very broad. We only know there is a difference in intensity, but we do not know how these measures are implemented. This loss of detail might affect the analysis. Research shows that ALMP resources are not always translated into high-quality services (Sztandar-Sztanderska, 2009) and the user–officer relation can influence the outcomes (Coletto and Simona, 2018). Biased estimates could be obtained due to the use of broad measures. Furthermore, causal claims cannot be made. As institutional configurations are strongly correlated over time, lagging the variables does not completely eliminate causality problems. Policies and socio-economic patterns are bi-causally related as policies might affect employment outcomes but, for instance, high unemployment rates might provoke a political demand to change the ALMP policy mix. Future research should focus on distilling the causal effects of ALMPs by using, for instance, instrumental variables or panel data. Although this study has limitations, we feel that useful and interesting results are obtained that contribute to discussions on the socio-economic consequences of educational attainment and the efficacy of ALMP programmes.

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Appendix

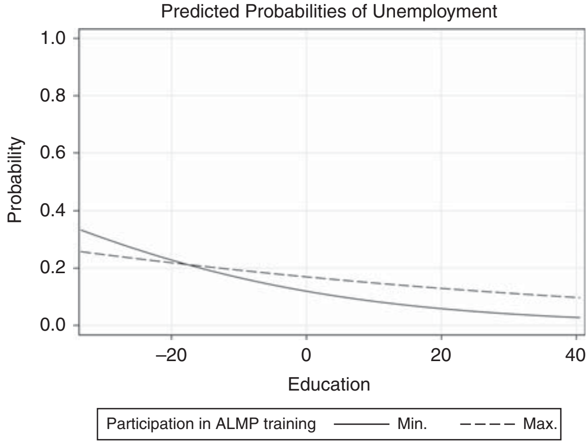

Figure A1. Predicted probabilities for unemployment based on education by participation in ALMP training

Sources: ESS 2010 (micro-data) and OECD (macro-data), own elaboration

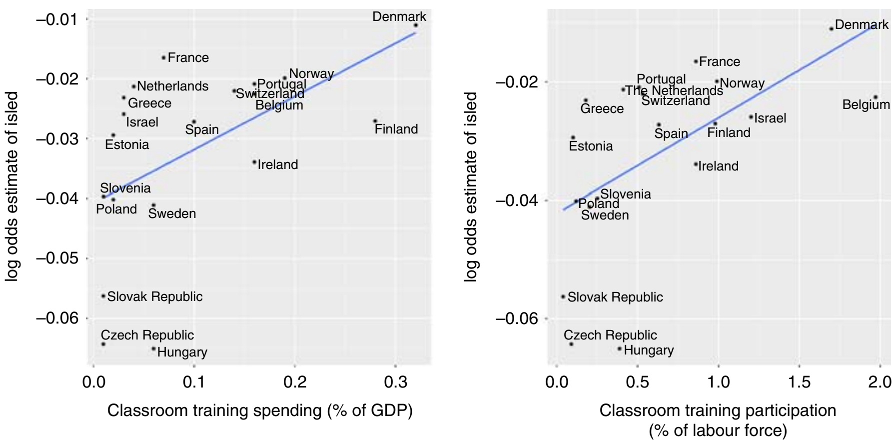

Figure A2. Within-country log odds estimates of unemployment predicted by education plotted against ALMP classroom training participation and spending

Sources: ESS 2010 (micro-data) and OECD (macro-data), own elaboration

Table AI. Multilevel logistic regression with Kenward–Roger correction on unemployment as dependent variable (ALMP spending indicators)

	Model 5			Model 6			Model 7			Model 8		
	Estimate	SE	OR	Estimate	SE	OR	Estimate	SE	OR	Estimate	SE	OR
Intercept	−3.244***	0.144		−3.246***	0.148		−3.219***	0.138		−3.240***	0.151	
Education_c	−0.029***	0.003	0.971	−0.029***	0.003	0.972	−0.029***	0.003	0.972	−0.029***	0.003	0.972
Training_c (spend)	1.841	1.127	6.302									
$\text{Education}_c \times \text{Training}_c$ (spend)	0.071*	0.026	1.074									
Classroom_c (spend)				1.358	1.415	3.886						
$\text{Education}_c \times \text{Classroom}_c$ (spend)				0.076*	0.032	1.079						
Workplace_c (spend)							7.092*	3.178	1,202.190			
$\text{Education}_c \times \text{Workplace}_c$ (spend)							0.109	0.089	1.115			
Hiring subsidy_c (spend)										0.241	1.198	1.273
$\text{Education}_c \times$ Hiring subsidy_c (spend)										0.011	0.031	1.011
Ethnic minority	0.387***	0.093	1.472	0.387***	0.093	1.473	0.387***	0.093	1.473	0.387***	0.093	1.473
Female	−0.134**	0.047	0.875	−0.134**	0.047	0.875	−0.132**	0.047	0.876	−0.132**	0.047	0.876
Age_c	−0.019***	0.002	0.982	−0.019***	0.002	0.982	−0.019***	0.002	0.982	−0.019***	0.002	0.982
Age_c^2	0.002***	0.000	1.002	0.002***	0.000	1.002	0.002***	0.000	1.002	0.002***	0.000	1.002
Trade union membership (ref: yes, currently)												
Yes, previously	1.173***	0.096	3.230	1.170***	0.096	3.221	1.164***	0.096	3.202	1.163***	0.096	3.201
No	0.974***	0.083	2.649	0.972***	0.084	2.642	0.959***	0.083	2.610	0.965***	0.083	2.625
Variance												
Intercept	0.2702			0.2944			0.2366			0.3085		
Education_c	0.0001			0.000107			0.000145			0.000146		
N	18,172			18,172			18,172			18,172		
Groups	19			19			19			19		

Notes: $*p < 0.05$; $**p < 0.01$; $***p < 0.001$
Sources: ESS 2010 and OECD, own elaboration

Table AII. Conditional (fixed effects) logistic regression with unemployment as dependent variable

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
$Education_c$	−0.0279***	−0.0278***	−0.0274***	−0.0274***	−0.0277***	−0.0273***	−0.0270***	−0.0274***
	(0.00149)	(0.00148)	(0.00146)	(0.00146)	(0.00156)	(0.00145)	(0.00145)	(0.00147)
$Education_c \times Training_c$ (spend)	0.0368**							
	(0.0137)							
$Education_c \times Training_c$ (part)		0.00579**						
		(0.00211)						
$Education_c \times Classroom_c$ (spend)			0.0433*					
			(0.0171)					
$Education_c \times Classroom_c$ (part)				0.00718*				
				(0.00280)				
$Education_c \times Workplace_c$ (spend)					0.0426			
					(0.0393)			
$Education_c \times Workplace_c$ (part)						0.0113**		
						(0.00435)		
$Education_c \times$ Hiring $subsidy_c$ (spend)							0.0166	
							(0.0167)	
$Education_c \times$ Hiring $subsidy_c$ (part)								0.00126
								(0.00102)
Ethnic minority	0.382***	0.383***	0.383***	0.384***	0.387***	0.386***	0.389***	0.391***
	(0.0927)	(0.0927)	(0.0928)	(0.0927)	(0.0926)	(0.0928)	(0.0927)	(0.0927)
Female	−0.130**	−0.129**	−0.130**	−0.128**	−0.127**	−0.129**	−0.127**	−0.127**
	(0.0472)	(0.0472)	(0.0472)	(0.0472)	(0.0472)	(0.0472)	(0.0472)	(0.0472)
Age_c	−0.0184***	−0.0186***	−0.0186***	−0.0187***	−0.0185***	−0.0186***	−0.0186***	−0.0186***
	(0.00202)	(0.00202)	(0.00202)	(0.00202)	(0.00202)	(0.00202)	(0.00202)	(0.00202)
Age_c^2	0.00187***	0.00187***	0.00188***	0.00188***	0.00186***	0.00186***	0.00186***	0.00186***
	(0.000162)	(0.000162)	(0.000163)	(0.000163)	(0.000162)	(0.000163)	(0.000163)	(0.000162)

(*continued*)

Table AII.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Trade union membership (ref: yes, currently)								
Yes, previously	1.176***	1.171***	1.174***	1.170***	1.173***	1.169***	1.168***	1.167***
	(0.0961)	(0.0960)	(0.0960)	(0.0960)	(0.0962)	(0.0961)	(0.0961)	(0.0962)
No	0.980***	0.972***	0.975***	0.969***	0.977***	0.969***	0.969***	0.969***
	(0.0833)	(0.0832)	(0.0833)	(0.0832)	(0.0834)	(0.0833)	(0.0834)	(0.0834)
N	18,172	18,172	18,172	18,172	18,172	18,172	18,172	18,172
Pseudo R^2	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078

Notes: Standard errors in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$
Sources: ESS 2010 and OECD, own elaboration