Lifelong Learning and Employment Outcomes: Evidence from Sweden

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Abstract

We study the relationship between adult education and training (AET) and employment in Sweden. Exploiting rich data from the Programme for the International Assessment of Adult Competencies, and using an inverse-probability weighted regression-adjustment estimator, we find that AET is positively related to the probability of doing paid work. This relationship is driven by non-formal, job-related AET, such as on-the-job training. We also find that the relationship – the strength of which increases with training intensity – is similar across different types of non-formal, job-related AET. The results suggest that policies stimulating relevant AET take-up have promise to secure higher employment.

Keywords: adult education and training; employment outcomes; PIAAC

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1. Introduction

In the past decades, knowledge requirements in developed countries' labour markets have changed radically, as technological innovation has displaced many low-skilled jobs and increased the required skills and competencies in jobs that continue to exist (e.g. ILO 2011). Sweden, an advanced export-orientated economy with a munificent welfare state, serves as an important case study in this respect. Between the 1970s and the early 2000s, the share of low-educated workers in low-skilled jobs in Sweden decreased from 48 per cent to 11 per cent, while the share of high-educated workers in high-skilled jobs increased from 28 per cent to 58 per cent (Tåhlin 2007). In 2016, only 4.8 per cent of Swedes were employed in jobs with no or low education requirements, the lowest figure in the European Union (Schermer 2017). In addition, a comparatively large share of Swedish employees report that their jobs have changed because of structural and technological transformation (OECD 2013a). Forecasts suggest these trends will continue and accelerate in the coming decades (Cefedop 2015). Due to the structural changes in the labour market, it is not surprising that Sweden has the lowest share of over-skilled workers, and one of the largest shares of under-skilled workers, among all OECD countries for which there are comparable data (OECD 2013a, 2016).

Overall, these developments indicate the importance of knowledge and skills for ensuring high employment and productivity levels in the future. While the school system will probably play a key role in this endeavour, adult education and training (AET) is also likely to be important. Indeed, people's knowledge and skills are not only developed in the school system but also at work and through learning later in life, which in turn may help people to maintain and continuously update their skills. And in knowledge-intensive labour markets like Sweden's, it is likely important for individuals to update their competencies during their working lives. In addition, Sweden has a long history of promoting lifelong learning among its citizens, both formal and non-formal, with the guiding principle that it should be open to all regardless of income (EAEA 2011). These features make the country an interesting context in which to analyse the relationship between AET and employment outcomes.

Yet, while there are reasons to believe that lifelong learning could play an important role for ensuring well-functioning labour markets, especially in contexts similar to Sweden's, little research investigates both formal and non-formal AET simultaneously, or separates the roles of job-related and non job-related AET. This is important in the Swedish context: in 2010–12, fully 65 per cent of the adult population underwent some form of adult education and training, with 52 per cent participating in job-related AET and 13 per cent participating in non job-related AET. In addition, the most common form of AET was non-formal, consisting of, for example, on-the-job training, courses, and workshops, which do not necessarily lead to official qualifications: 60 per cent of the adult population underwent non-formal AET and 14 per cent underwent formal AET.[1] Whether or not the former type is related to labour-market outcomes in the Swedish context has not yet been investigated.

In this paper, we therefore analyse how lifelong learning is related to individuals' employment prospects in Sweden. Using data from the 2012 round of the Programme for the International Assessment of Adult Competencies (PIAAC) allows us to adjust for an

[1] These calculations, which do not include students aged 16–24 who are in their first formal cycle of studies, are carried out using micro-level data from the OECD's (2017) PIAAC database, which we utilise in this paper. The data are derived from questions enquiring whether respondents studied for (1) any formal qualification at primary, secondary, university, or post-secondary level, and (2) whether they participated in non-formal education through 'Courses conducted through open or distance education, 'Organised sessions for on-the-job training or training by supervisors or co-workers', 'Seminars and workshops', and/or 'Other courses or private lessons'. Job-related AET is defined as training that individuals report having undergone for the purposes of improving their employment chances in general. Statistics Sweden (2014) reports very similar figures using other data.

unusually large number of important observable characteristics, including cognitive skills, formal education levels, and work history in the year prior to the survey. By adjusting for work history in the year prior to the survey, we effectively study the employment effects of AET only among people who did paid work during the period in which their participation in AET is measured. In combination with our exploiting an inverse-probability weighted regression-adjustment estimator, this increases the probability, but does not guarantee, that our methodology overcomes bias arising from individual selection into AET. While we are unable to entirely rule out omitted-variable bis, given the paucity of research analysing the effects of different types of AET on employment outcomes, we believe the paper provides an important contribution to the understanding of the relationship between AET and employment.

Furthermore, our tests show that the weighting procedure balances the rich covariates across the main treatment and control groups, suggesting our main model is well specified. We also show essentially identical results when we exclude all covariates apart from age, gender, and work history in the year prior to the survey, suggesting differences in other covariates – including social background, cognitive skills, and formal educational levels – that affect both the probability of engaging in AET and the probability of doing paid work are ironed out using this sparse specification.[2] Still, as we cannot conclusively rule out omitted-variable bias, caution regarding the causal interpretation of the results is naturally warranted and future research should further investigate the effects of AET

[2] While it would also be interesting to study the effect of AET on earnings, we refrain from doing so in this study. This is partly because the PIAAC dataset does not include any measure of earnings history, which is likely key to ensure that the conditional independent assumption holds – just as an indicator of work history appears key for this purpose in this paper. Also, the Swedish PIAAC dataset only includes information of earnings in deciles, which is too coarse to permit a rigorous analysis of how AET affects earnings.

using quasi-experimental variation to address potential selection on unobservable characteristics at both the individual and employer levels.

Our findings show that individuals who participated in AET in the year prior to the survey are about 4 percentage points more likely to do paid work in the week before the survey took place than comparable individuals who did not undergo AET. Intriguingly, the findings are entirely driven by job-related AET, which appears to raise the probability of working by 6 percentage points – and this is in turn entirely driven by non-formal, job-related AET, which appears to raise the probability of working by about 8 percentage points. If anything, the positive relationship is even stronger when analysing the probability of working full time instead of the probability of doing any paid work at all. And while we find some evidence that the expected relationship among participants of non-formal, job-related AET is slightly stronger than the expected relationship among non-participants, the latter is considerable as well.

We further find that the relationship is very similar across different types of non-formal, job-related AET, which may also suggest that potential sources of omitted-variable bias that are specific to certain types of such AET do not drive the results. Interestingly, the importance of non-formal, job-related AET appears to vary depending on training intensity: the relationship strengthens with the number of such AET activities in which individuals participated. Yet non-formal, non job-related AET and formal AET of either type have no relationship with employment outcomes. Several robustness tests support these conclusions.

Of course, it is important to note the context of our findings: we analyse data collected in Sweden during the country's economic recovery following the 2008 financial crisis. Since the effects of AET on employment outcomes may well be country specific and interact with the business cycle, future research should investigate the generalisability of the results in these respects. Still, research analysing data from other countries does often suggest positive effects of training on labour-market outcomes, which would support the idea that the relationship found here may be generalisable to other contexts. At the very least, the findings indicate that policies stimulating higher non-formal, job-related AET take-up have promise as a way to increase employment in similar settings – and reforms to increase access to lifelong learning should therefore be considered. This includes reforms to increase employers' incentives to give employees opportunities to pursue non-formal, job-related AET. However, more research into what works in this respect is necessary.

The paper proceeds as follows. Section 2 discusses the theoretical mechanisms linking AET and employment outcomes and reviews the empirical literature; Section 3 outlines the data analysed; Section 4 discusses the methodology employed; Section 5 presents the results; and Section 6 concludes.

2. Theory and prior literature

According to economic theory, individuals and companies invest in education and training in order to improve human capital and in this way raise their earnings and productivity respectively (Becker 1964). Empirical research has established that education has positive effects on labour-market outcomes, and there is much to suggest that an important part of this impact operates via higher human capital (e.g. Bhuller et al. 2017; Brunello et al. 2016). Similarly, research finds that average knowledge levels across countries' populations are strongly related to economic growth (Hanushek and Woessmann 2015). Since education does not only create value for the individuals who participate in it, there are compelling reasons for the government to finance and stimulate investments in knowledge and skill development (see McMahon 2010).

There are also reasons to believe that different forms of AET may be especially important for maintaining and developing individuals' human capital over the course of their working lives, once they have completed their formal education at school and university. AET makes the labour market and competence provision more effective, since it 'facilitates career shifts if there are changes to demand in the labour market or in individuals' health' (Stenberg 2016, pp. 20–21). Adult education does not have to be formal to improve individuals' human capital – also non-formal education is important. As Statistics Sweden (2013, p. 41) writes:

> The formal education system is not the only setting in which literacy, numeracy, and digital problem-solving skills are developed. Learning also occurs in several other settings, such as within the family, in the workplace, or during recreational activities and self-studies. Adults who do not utilise their skills sufficiently at work or during leisure time risk losing their competencies and abilities. The longer since a person completed his or her studies, the weaker is the direct relationship between the level of formal education and the person's skills. For older people, other factors than formal education levels matter greatly for skill development, such as the type of vocation, opportunities for learning in the workplace, and the social environment.

In other words, it is plausible that AET may have positive effects on individuals' labour-market outcomes. Indeed, there is empirical research suggesting that formal adult education has positive effects on salaries and employment (e.g. Jacobson et al. 2005a, 2005b; Lee and Gill 1997; Light 1995; Monks 1997; Pischke 2001; Stenberg 2016). However, the results are still mixed. For example, British research shows that formal education at lower- and upper-secondary levels in adulthood only generates higher incomes among men with low initial education. Still, specifically vocational education does seem to increase the probability of employment more generally (Jenkins et al. 2003). Recent Swedish studies using a similar methodology as this paper tend to find positive effects on labour-market outcomes of formal adult education at the primary and secondary levels as well as employment-training programmes, at least in a slightly longer-term perspective (Bergemann and van den Berg 2014; Stenberg 2016; Stenberg and Westerlund 2015). The evidence on non-formal learning, such as personnel training, is also somewhat mixed, but again sometimes shows positive effects (e.g. Albert et al. 2010; Ariga and Brunello 2006; Bassanini et al. 2005; Blundell et al. 1999; Dearden et al. 2006; Haelermans and Borghans 2012; Georgiadis and Pitelis 2016; Konings and Vanormelingen 2015; Pischke 2001; Lynch 1992; Ruhose et al. 2019; Schwerdt et al. 2012; Vignoles et al. 2004).

However, to the best of our knowledge, no research has analysed the effects of formal and non-formal AET on employment simultaneously – or investigated the effects of non-formal AET in Sweden in any way at all. Similarly, no studies separate the effects of job-related from non job-related AET in the same analysis in this respect.[3] These gaps are important since the impact of these various types of AET may differ. For example, AET that focuses on specifically job-related skills, which individuals undergo for job-related reasons, may have a more positive impact on employment outcomes compared with other types of AET. Also, formal education may better prepare individuals for the labour market than non-formal education, if the former provides more structured and rigorous

[3] However, there is research separating the effects of specifically on-the-job work-related training from off-the-job work-related training on wages. For example, Lynch (1992) studies the impact of on-the-job as well as off-the-job training – with the latter provided through apprenticeships and for-profit institutions – on wages among young, non-university graduates, finding positive effects of both types, while Pischke (2001) finds imprecise evidence suggesting that the wage returns to off-the-job training are larger than the returns to on-the-job training. Another study finds that the wage returns to both on-the-job and off-the-job training is dependent on years of schooling (Ariga and Brunello 2006).

training than the latter. On the other hand, non-formal education may be more practically orientated, and thus generate skills that are more relevant in the labour market. To explore such potential heterogeneity, it is important to analyse the effects of different types of AET. More research is also generally necessary, since most existing studies are quite old, which means that they do not necessarily reflect the effects of AET in today's labour markets, and often use research methods that ignore potential selection bias.

3. Data

To study the relationship between AET and employment outcomes in Sweden, we exploit micro-level data from PIAAC. PIAAC surveys the adult population's literacy, numeracy, and problem solving in technology-rich environments. It also collects rich information on respondents' backgrounds and how they utilise their skills. In the first round, which was carried out in 2012, there were 166,000 participants aged 16–65 from 24 countries. In the 2016 round, 14 additional countries participated.[4] Table A.1 outlines the descriptive statistics of the data analysed.

The Swedish sample in PIAAC 2012 was composed of 10,000 individuals, who were randomly drawn from the adult population aged 16–65. Data were collected between August 2011 and May 2012. The non-response rate was 55 per cent, which means that the sample in the end was composed of 4,468 individuals.[5] Using the sample weights provided, it is nevertheless possible to ensure that this sample is representative of the targeted population. Indeed, despite the non-response rate, the OECD (2013b) found the Swedish results to be reliable. However, we exclude all students aged 16–24 who are in

[4] In contrast to many international assessments at the school level, PIAAC is not carried out continuously in the same countries. To date, each country has only participated once, with the exception of the United States (which participated in both the 2012 and 2016 rounds).

[5] Technically, the final sample was composed of 4,469 respondents, but due to one observation with no values in the database, the number available for analysis is 4,468.

their first formal cycle of studies, since they do not form part of the AET population. This decreases the available sample to 3,888 individuals.[6]

3.1. *Adult education and training*

To analyse the effects of lifelong learning, we exploit a variable in the PIAAC database, which indicates whether respondents participated in some form of adult education and training in the 12 months before the survey was carried out. This variable is derived from questions enquiring whether respondents studied for (1) any formal qualification at primary, secondary, university, or post-secondary level, and (2) whether they participated in non-formal education through 'Courses conducted through open or distance education, 'Organised sessions for on-the-job training or training by supervisors or co-workers', 'Seminars and workshops', and/or 'Other courses or private lessons'. Individuals who did participate in any form of AET are given a value of 1, while those who did not are given a value of 0. This variable does not include education undergone by students aged 16–24 who are in their first formal cycle of studies, which means that it only picks up different types of AET. This is useful since the average effect of different types of AET has not previously been evaluated in Sweden.

Yet it is also important to investigate heterogeneous effects depending on the type of AET pursued. For example, it is plausible that job-related AET affects employment outcomes differently compared with non job-related AET. In PIAAC, respondents were asked whether the AET in which they participated was 'job related', which is defined as AET that individuals report having undergone for the purposes of improving their employment chances in general. The OECD has constructed two separate indicators for

[6] However, our preferred inverse-probability weighted regression-adjustment estimator, discussed in Section 4, automatically excludes a few individuals who have/have not undergone AET, but whose values on the covariates do not overlap with any of the individuals who have not/have undergone AET.

job-related and non job-related AET respectively, which we utilise in our analysis.[7] Similarly, the effects of AET may depend on whether it is delivered through the formal education system or provided informally outside that system. We thus separate job-related and non job-related AET into their formal and non-formal components, again based on the above statements, creating four different AET categories in total.[8] We also separate each non-formal AET category that we find to be related to employment into its four components.[9] Finally, to study whether any detected effects vary by training intensity, we create a variable indicating the number of AET activities in which individuals participated, for each AET category that we find to be related to employment.

3.2. Employment outcomes

The respondents were asked whether they did any paid work in the week before the survey was carried out. Those who reported doing any paid work for at least an hour are given the value of 1, while those who did not are given a value of 0. We utilise this indicator as our main dependent variable. However, in one robustness test, we also use an indicator for whether respondents worked full time at the time of the survey. Those

[7] It is not possible for individuals to simultaneously report that they underwent both job-related and non job-related, formal AET, or both job-related and non job-related, non-formal AET, but it is possible for them to report that they underwent different combinations of formal and non-formal AET. The OECD's assignment of individuals to the job-related and non job-related categories is based on, firstly, the type of formal AET they underwent, and, secondly, the type of non-formal AET they underwent. For example, individuals who underwent non job-related, formal AET as well as job-related, non-formal AET are assigned to the non-job related AET category. In an unreported robustness test, we instead created a separate indicator for individuals who underwent both job-related, formal AET and non job-related, non-formal AET, or non job-related, formal AET and job-related, non-formal AET (about 2 per cent of the sample), but found little support for interaction effects in this respect.

[8] We follow the OECD's method of assigning individuals to the different categories by, firstly, the type of formal AET they underwent, and, secondly, the type of non-formal AET they underwent (see the previous footnote). In an unreported robustness test, we created a separate indicator for respondents who underwent both formal and non-formal AET (about 9 per cent of the sample), but found little support for interaction effects in this respect.

[9] In this analysis, to be able to distinguish differential effects, we exclude individuals who participated in more than one non-formal AET component, for each overall category found to be related to employment. In an unreported robustness test, we further excluded individuals who also underwent some form of formal AET, but the results were essentially identical.

who report that they are full-time workers are given a value of 1 and those who do not – including part-time workers – are given a value of 0. This allows us to investigate whether the effects of AET on the probability of working full-time differ from the effects on the probability of doing any work at all.

3.3. Covariates

In the analysis, we adjust for a number of relevant covariates. These include indicators for the respondents' background: age, gender, first- and second-generation immigration status, whether Swedish is their native language, years spent in Sweden, the number of books at home (6 intervals), maternal educational level (3 levels), paternal educational level (3 levels), and the number of people in the household (capped at 6 people). Also, we control for the participants' formal educational level, in years of schooling, and their literacy and numeracy scores in PIAAC. This is important since Swedes with higher levels of education and cognitive skills tend to be more likely to pursue lifelong learning than people with lower levels of education and cognitive skills (see Bussi and Pareliussen 2015).[10]

Furthermore, in the preferred model, we include an indicator for whether or not respondents carried out paid work in the 12-month period prior to the survey. Since all respondents who worked in the week before the survey by definition also did so at some

[10] Some of the control variables, such as years of schooling, test scores and the number of books at home, may be partly endogenous to AET undertaken in the year prior to the interview. If so, by including these variables as covariates, we may adjust for some of the mechanisms behind the effect of AET. However, since our research strategy hinges on adjusting for rich observable characteristics to make the conditional independence assumption hold, we believe this is a risk worth taking. Furthermore, the variables in question are positively correlated with both AET and employment, meaning that we are less likely to find a positive effect once holding them constant. In other words, we are more likely to err on the side of caution than bias the estimates in favour of the hypothesis that AET has positive effects on employment outcomes. Finally, in robustness tests, we also show that results are essentially identical when only including age, gender, and an indicator of paid work measured in the same period as the AET indicator, showing that potentially endogenous covariates do not drive the findings.

point in the year preceding it, our comparison takes into account whether or not currently non-working respondents did paid work at some point in the previous year. This means that we effectively only analyse people who did paid work during the period in which their participation in lifelong learning is measured, studying the probability that they also did paid work in the week before the survey.[11] We also include an indicator for whether or not respondents have done any paid work in their lives at all.[12] In robustness tests, we further include industry dummies as well as indicators for the geographical region in which respondents live.[13]

Given that we are able to adjust for unusually rich data, we control for many important factors that explain selection into AET at the individual level. As we discuss in Section 4, given the data available, it is more difficult to do so at the employer level, and adjusting for employer-level indicators would also likely introduce endogeneity problems into our model. While we therefore cannot make strong claims regarding the causality of the estimates in the paper, given the paucity of research analysing the effects of different types of AET on employment outcomes, we believe it still provides an important contribution to understanding of the relationship between AET and employment.

Another potential issue concerns the functional form of the relationship between the observable characteristics and employment, which is far from clear. This makes it important to create treatment and control groups that have comparable values on the

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[11] However, we still include individuals who did not do paid work in the 12-month period prior to the survey in the analysis. This is because these individuals contribute to the inverse-probability weighted regression-adjustment estimator's first step, which is used to construct the weights utilised in the second step, as discussed in Section 4. Nevertheless, results are unsurprisingly almost identical if we exclude individuals who did not do paid work in the 12-month period prior to the survey.

[12] Individuals who have never done paid work contribute to the inverse-probability weighted regression-adjustment estimator's first step, as discussed in Section 4. However, as noted in the previous footnote, results are essentially identical if we exclude these individuals.

[13] Following previous research, we replace missing values for the covariates with the sample means and include separate indicators for missing values in the regressions (see Hanushek and Woessmann 2011).

observable characteristics that we seek to hold constant. The next section discusses the method we utilise to be able to do so.

4. Method

For the purposes of studying the relationship between all types of AET and employment outcomes, consider the following OLS model:

$$e_i = \alpha + \beta_1 aet_i + \beta_2 x_i + \varepsilon_i \qquad (1)$$

where e_i is the indicator for paid work in the week before the survey; aet_i denotes the AET dummy; x_i is a vector of observable covariates; and ε_i is the error term. The model's assumption is that $Cov(aet_i, \varepsilon_i | x_i) = 0$ so that the average treatment effect is given as $E[e_i | x_i, aet_i = 1] - E[e_i | x_i, aet_i = 0] = E[e_{1i} - e_{0i} | x_i]$. However, if x_i does not include all variables that impact both e_i and aet_i or if e_i affects aet_i directly, it would mean that $Cov(aet_i, \varepsilon_i | x_i) \neq 0$ and the results will suffer from endogeneity bias (Angrist and Pischke 2009).

Such endogeneity may arise from omitted individual characteristics. For example, high (unobserved) ability may explain both AET take-up and employment outcomes. Similarly, participation in training may be due to omitted employer/workplace characteristics, such as employer beliefs about the importance of training (for all or specific employees) as well as general job quality. For example, it may be the case that higher-quality workplaces are associated with more opportunities for individuals to participate in AET. If so, any positive relationship between AET and employment outcomes may be due to the general effect of workplace quality rather than AET itself.

To estimate causal effects, it is therefore necessary to either obtain quasi-experimental variation in the take-up of AET or have access to enough observable characteristics to make the conditional independence assumption plausible. In our data, it is not feasible to obtain quasi-experimental variation, especially since we seek to investigate potential heterogeneous effects across different types of AET. And while we do believe that our dataset is rich enough to adjust for the most important factors behind individual selection into AET, it is more questionable whether it is rich enough to adjust fully for variables that explain workplace/employer selection into offering employees' access to AET.[14] Certainly, to some extent, adjusting for individual-level variables is likely to indirectly adjust for variables explaining AET access at the employer level. Nevertheless, the individual-level control variables may not be sufficient to iron out all relevant variables at the employer level.

Yet, even if we had access to relevant variables at the workplace level, adjusting for them would risk creating endogeneity problems. For example, higher job quality may well be the result of having more access to AET – and adjusting for it would then likely introduce 'bad controls' into the model (see Angrist and Pischke 2009). Controlling for individual-level variables that help explain selection into jobs of different quality, with different accessibility to AET, is therefore more straightforward than to also attempt to adjust for differences in workplaces.

Still, research indicates that parametric models with rich controls may in fact increase bias, if the functional form of the relationship between the controls and the outcome is not adequately captured (see Heckman et al. 1998; Rubin 2001, 2008; Rubin and Thomas 2000). It is thus likely important to balance the distribution of the control variables across the treatment and control groups. We do so using an inverse-probability weighted regression-adjustment estimator, or IPWRA (see Wooldridge 2010). This estimator has

[14] It is not possible to adjust for such variables, since only those who are currently engaged in paid work answer questions of relevance to the issue of workplace quality.

recently been exploited for similar purposes, such as in analyses of the effects of vocational education, bullying, and personality traits on various outcomes (see Brunello and Rocco 2017; Gorman m.fl. 2019; Mendolia and Walker 2015).[15] The inverse-probability weighted regression-adjustment estimator predicts for each individual all potential employment outcomes for all different AET types analysed, using information from individuals with similar observable characteristics who did not undergo any AET (or who underwent an alternative type of AET than the individual in question). This means that we can study all average treatment effects of the different forms of AET separately in the same model.

In other words, the conditional independence assumption for all possible AET types a gives us $E[e_i(a)|x] = E[e_i(a)|a_i(a) = 1, x]$, where $a_i(a) = 1$ denotes individuals undergoing AET type a. Once we adjust for x, the average treatment effect of a compared with the benchmark a' – which denotes either individuals who have not undergone any AET or those who have undergone other types of AET than a – is obtained by effectively comparing the conditional employment rate among individuals who underwent a with the conditional employment rate among individuals with benchmark a':

$$E[e_i(a)|a_i(a) = 1, x] - E[e_i(a')|a_i(a') = 1, x] = E[e_i(a) - e_i(a')|x] \tag{2}$$

The inverse-probability weighted regression-adjustment estimator is thus composed of two steps. The first step estimates the probability of undergoing AET a from observable characteristics, using a logit model or, when analysing the effect of different types of AET, a multinomial logit model. The second step then estimates the effect of AET

[15] Our outline of the estimator draws on Brunello and Rocco's (2017, pp. 338–342) discussion.

a on the employment outcomes using a linear model, with the inverse probability of undergoing AET a as weight, while also including all covariates.[16]

In practice, the estimator thus compares individuals' actual employment outcomes after undergoing AET a with the counterfactual outcomes the same individuals should have obtained under benchmark a'.[17] To ensure that the weighting procedure balances the covariates across the main treatment and control groups, which is important for drawing valid inferences (see Rubin 2008), we use Imai and Ratkovic's (2014) over-identification test for covariate balance and also present the raw and weighted differences as well as variance ratios for the two groups.[18] To ensure that our estimates are relevant for the population from which the sample is drawn, we include the sample weights provided in the PIAAC database in the first step of the model.[19]

Using the methodology outlined above, the identification assumption would thus be that assignment to different types of AET is as good as random conditional on the

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[16] Since the model is dependent on respondents having similar values on the covariates, it is only possible to study AET effects among people in the treatment and control groups for which the covariates overlap. To determine such overlap, we use the default tolerance level in the *teffects* command in STATA. As discussed in Section 5.2, Figures A.1–A.4 in the Appendix show graphically that there is generally sufficient overlap in the main models. In robustness tests, to increase overlap with the density of predicted probabilities of not undergoing any AET further, and to ensure that our results are not dependent on a small number of observations, we also trimmed the sample and re-estimated the models. As highlighted in Section 5.2, despite dropping about 60 per cent of the observations, the results are essentially identical.

[17] While the assumptions are essentially the same as in propensity score matching, the latter does not allow analyses of multiple treatments simultaneously. In robustness tests, we instead used regular nearest matching to study the average relationship between AET and employment as well as the relationship between employment and each category of training we find to be related to employment. Similarly, we utilised entropy balancing, which achieves complete balance in terms of means, variances, and skewness in single treatment and control groups by using weights constructed through data pre-processing. This estimator has been found to balance treatment and control groups more efficiently than matching estimators (see Hainmuller 2012; Hainmuller and Xu 2013). As discussed in Section 5.2, the results from these alternative estimators are very similar to the equivalent results from the IPWRA estimator.

[18] The over-identification test can only be carried out in analyses with one treatment group, and we thus only present these statistics for the main model analysing the average effect of all types of AET, as well as for models separately analysing the types of training that have effects on employment outcomes.

[19] While literacy and numeracy scores in PIAAC are estimated from ten 'plausible values' derived from multiple imputations, and replicate weights are used to adjust for sampling error (see OECD 2013b), we use the average of all plausible values for each subject and regular robust standard errors. This is to estimate both the inverse-probability weighted regression-adjustment estimator and the covariate balance test correctly. However, the OLS results are identical if we estimate the regressions for each plausible value separately and use replicate weights to adjust the standard errors, suggesting these adjustments matters little – which is supported by prior research analysing similar survey structures (see Jerrim et al. 2017).

covariates outlined in Section 3.3. While we cannot conclusively rule out the possibility of selection bias due to unobservable characteristics, as discussed above, we carry out robustness tests to rule out some important threats to causal inference. These robustness tests include adding indicators for industry and geographical region to the equation, and excluding all covariates apart from age, gender, and the dummy indicating whether respondents carried out any paid work in the previous year. If the results are very similar despite adding potentially important predictors of employment outcomes, and when excluding predictors that are normally crucial for such outcomes – including socio-economic background, cognitive skills, and years of schooling – it may strengthen the case that selection into AET is adjusted for appropriately. We also analyse whether the relationship between any AET type that we find to be related to employment outcomes varies depending on training intensity. If the relationship is 'dose dependent', it at least indicates that more training predicts better employment outcomes also among individuals who all participate in some form of AET.

Certainly, the above intuition is far from foolproof. For example, if the effect size is very similar when excluding most control variables, it may also instead indicate that the main specification and the sparser version are equally biased. Also, selection bias may increase with stronger training intensity, for example if there is a linear relationship between unobserved ability and training intensity. It is therefore impossible to conclusively interpret a dose-dependent relationship as evidence that the model picks up causal effects, although it would be consistent with such an interpretation. Overall, therefore, as discussed earlier, caution in terms of causal conclusions is warranted and future research should further investigate the effects of AET using quasi-experimental variation to address potential selection on unobservable characteristics.

5. Results

As a starting point, Columns 1–3 in Table 1 show the results from a regular OLS model when including different combinations of control variables. The estimates indicate that AET is positively associated with paid work, regardless of which controls we include. In the full model in Column 3, undergoing some form of AET is associated with a 5 percentage point increased likelihood of doing paid work. Thus, our initial results indicate that there is a positive correlation between AET, as measured in PIAAC, and employment outcomes in Sweden.

[INSERT TABLE 1 HERE]

Turning to the estimates from the inverse-probability weighted regression adjustment model in Columns 4–6, we note that the results are in fact very similar compared to the OLS results: in the full model in Column 6, undergoing some form of AET increases the probability of doing paid work by 4 percentage points.[20] Since this model is most likely to pick up the causal impact of AET, we take this to be our main estimate. Nevertheless, the headline finding is similar regardless of whether we assume that the relationships between the covariates and the probability to do paid work are linear, using the OLS model, or do not make any assumptions of the functional form of these relationships, using the IPWRA model.[21]

However, as noted in Section 4, it is important to analyse whether the weighting estimator balances the covariates across the treatment and control groups. Table 2

[20] This may be compared with the coefficient of years of schooling, which in the equivalent OLS model in Table 1 in fact only has a weak, statistically insignificant positive relationship with the probability of doing paid work. However, the coefficient of literacy scores is positive and statistically significant in this model, indicating that a one standard deviation increase in literacy scores is associated with a 4 percentage point increase in the probability of doing paid work.

[21] This finding is not that unusual in the field and may reflect the sometimes rather subtle differences between OLS and propensity-score estimators, especially when analysing large-scale datasets and including rich controls (see Goodman and Sianesi 2005; Mendolia and Walker 2015).

presents results from the balance tests following the full model in Column 6 in Table 1. There is no doubt that the raw differences between treatment and control groups are significant in many cases, highlighting the importance of ensuring that our weighting procedure balances the groups appropriately. Indeed, the estimates indicate that our method worked as intended: the weighted differences in means and variances are small, and the over-identification test for covariate balance displays a value of 0.94, suggesting we comfortably fail to reject the null hypothesis of balanced covariates. Overall, the results thus suggest that the treatment and control groups are very similar in terms of the variables adjusted for in the model.

[INSERT TABLE 2 HERE]

5.1. Does the relationship differ depending on AET type?

Does the relationship between AET and employment depend on whether the AET is job-related or non job-related and whether it is formal or non-formal? Table 3 shows results from the inverse-probability weighted regression-adjusted model corresponding to Column 6 in Table 1. The first panel presents results from models analysing job-related and non job-related AET separately, while the second panel presents results from models further separating job-related and non job-related AET into their formal and non-formal components.

The results in the first panel show that the relationship between AET and employment is entirely driven by job-related AET, which raises the probability of doing paid work by 6 percentage points. The coefficient of non job-related AET is small and statistically insignificant – and its difference compared with the coefficient of job-related AET is statistically significant, when using the latter as the benchmark category in the IPWRA estimator. Interestingly, when we separate the coefficients along the formal and non-formal dimensions, we find that job-related, non-formal AET is related to an 8 percentage point higher probability of employment, while the other types have no relationship with employment at all: the coefficients for the two types of formal AET are negative, but not by a statistically significant margin. However, the differences between job-related, non-formal AET and all other types of AET are statistically significant, when using the former as benchmark category.

Overall, our findings suggest that job-related, non-formal AET, such as on-the-job training, dominates other AET types in terms of the relationship between AET and employment. As noted in Section 2, since such training is undertaken for the specific purpose of improving individuals' job prospects generally, and may well be more practically orientated than formal courses, this finding is perfectly reasonable.

[INSERT TABLE 3 HERE]

But are all forms of job-related, non-formal AET equal? To investigate this, we separate job-related, non-formal AET into its four separate components, as outlined in Section 3.1. The results are presented in the third panel in Table 3. We find that the coefficient of job-related, non-formal AET is similar across the four components, suggesting that its relationship with employment is not driven by any particular component of such training. The point estimate is the largest for open or distance education and the smallest for on-the-job training and other courses or private lessons, but these differences are far from statistically significant when using the different components as benchmark categories in the IPWRA estimator.[22] The homogeneous findings in this respect also suggest that

[22] This also holds true when excluding individuals who did not participate in any form of job-related, non-formal AET and using 'On-the-job training' as benchmark category. While the differences between the separate components of job-related, non-formal AET and non job-related, non-formal AET as a whole are not statistically significant in Panel 3, this is not surprising since the disaggregation of the job-related, non-formal AET category naturally decreases the precision of the separate estimates. Also, as highlighted in footnote 9, the number of observations decrease in Panel 3 because, in order to separate the effects of the

possible sources of omitted-variable bias that are specific to certain types of job-related, non-formal AET are unlikely to drive the results.[23]

5.2. Robustness tests

To test the robustness of our findings, we (1) present results from models analysing the effects of the different types of AET on the probability to do full-time work, (2) restrict the sample to individuals aged 35 and over, (3) include industry and geographical dummies as covariates, and (4) exclude all covariates apart from age, gender, and the dummy indicating whether or not respondents carried out any paid work in the 12-month period prior to the survey. Also, since we find that job-related, non-formal AET drives the overall positive relationship with the probability to do paid work, we (5) exclude respondents who have undergone other types of AET from the analysis, and carry out the over-identification test for covariate balance for this particular type of training. The results from these robustness tests are reported in Table 4.

[INSERT TABLE 4 HERE]

Regardless of model, we obtain results that are consistent with our main estimates. Interestingly, the relationship between AET and the probability of working full time in fact appear larger than the relationship with the probability of doing any paid work at all. It is noteworthy that the model excluding all controls apart from age, gender, and the

different job-related, non-formal AET components, we exclude individuals who participated in more than one such component simultaneously.

[23] For example, the findings largely rule out one potential source of bias: individuals undergoing on-the-job training as preparation for a new position for which they have already been selected. Such individuals undergo AET as a result of getting the new position rather than vice versa. While we believe adjusting for paid work in the previous year is sufficient to deal with this potential issue, the fact that we find very similar effects across all types of job-related, non-formal AET further indicates it is not an important problem. This conclusion is also supported by unreported analyses in which we found essentially identical effects of job-related, non-formal AET when excluding all individuals who underwent such AET mainly (1) because they were obliged to do so or (2) to do their jobs better and/or improve their career prospects, either of which would presumably apply if AET was undertaken as a result of getting a new position.

dummy indicating whether or not respondents carried out any paid work in the previous 12-month period displays almost identical results as the main estimates, suggesting it effectively irons out differences in other covariates – including social background, cognitive skills, and formal educational levels – that generally are assumed to affect both the probability of engaging in AET and of doing paid work. Also, as displayed in Panel 4, the coefficient of job-related, non-formal AET is essentially identical when we exclude respondents who have undergone other types of AET. The test for covariate balance shows a p-value of 0.96, suggesting that the weighting procedure also works as intended for the type of training that drives our main findings. Overall, the findings thus further strengthen the idea that specifically job-related, non-formal AET has a positive relationship with the probability of doing paid work, while other types have no consistent relationships in this respect.

In further robustness tests, we (1) checked the overlap assumptions graphically, (2) trimmed the sample to maximise overlap with the density of the predicted probabilities of not undergoing any AET at all – which is the baseline category – and then (3) re-estimated the main models using the trimmed samples. The results are displayed in Figures A.1–A.4 and Table A.2 in the Appendix. There is considerable evidence of overlap in the untrimmed models – which should be expected since observations that violate the default overlap assumption have been dropped automatically – which generally increases further in the trimmed samples.[24] And despite dropping about 60 per cent of the

[24] The only (partial) exception is the probability of undergoing non job-related, formal AET in the untrimmed model. While there is overlap in this case as well, large proportions of the probability mass of the control and alternative treatment densities are close to zero. Yet, as displayed in Table A.2, the results are very similar when restricting the sample to observations below the 40th percentile of the predicted probabilities of not undergoing any AET, which decreases this problem significantly. Furthermore, we also re-estimated all relevant models with individuals undergoing non job-related, formal AET excluded, and the estimates for the other categories were essentially identical.

observations, the results are essentially identical in comparison to the main estimates. We therefore conclude that our findings are robust to trimming the sample considerably.

Finally, to test the robustness of the results to the choice of estimator, we instead used regular propensity-score matching to study the average relationship between AET and employment as well as the relationship between job-related, non-formal training with employment, compared with no training at all. Similarly, we utilised entropy balancing, which achieves complete balance in terms of means, variances, and skewness in single treatment and control groups by using weights constructed through data pre-processing. This estimator has been found to balance treatment and control groups more efficiently than matching estimators (see Hainmuller 2012; Hainmuller and Xu 2013). As shown in Table A.3, the results from these alternative estimators are very similar to the equivalent results from the IPWRA estimator, displaying that our main findings do not depend on specific quirks of the latter.

5.3. Does the relationship vary depending on training intensity?

It is possible that the effect of job-related, non-formal AET varies depending on training intensity; participating in more AET activities may theoretically yield larger benefits in the labour market. To explore this issue, we analyse the relationship between employment and participation in one job-related, non-formal AET activity, two such activities, three-to-five such activities, and more than five such activities separately.[25] Table 5 shows the results.[26] They indicate that there is indeed a 'dose-dependent' relationship between the number of job-related, non-formal AET activities in which

[25] These categories roughly correspond to observations in the 25th percentile and below, between the 25th and the 50th percentile, between the 50th and the 75th percentile, and in the 75th percentile and above, among people who participated in at least one job-related, non-formal activity.

[26] In order to accurately display the 'dose-dependent' relationship, we report coefficients with three decimal places, instead of two, in Table 5 specifically.

individuals have participated and the probability that they do paid work: the coefficient increases with each step change on the variable. For example, while participating in one activity is related to a 6.5 percentage point higher probability of doing paid work, participating in five or more activities is related to 11.1 percentage points higher likelihood of doing paid work. And while the margin between each step change is not generally statistically significant, the effect of participating in five or more activities specifically differs from the effects of all other categories by a statistically significant margin.

[INSERT TABLE 5 HERE]

The results thus support the idea that the relationship between job-related, non-formal AET and employment depends on training intensity. Moreover, since this comparison focuses on differences in employment outcomes among individuals who have all participated in at least one job-related, non-formal AET activity, they may suggest that general selection into this type of AET at the individual level does not explain the estimates in Tables 3 and 4.[27] As noted in Section 4, the results certainly do not entirely rule out selection bias, but it is at least consistent with such an interpretation.

5.4. *Comparing the average treatment effects on the treated and the untreated*

While we have thus far focused solely on the average treatment effect of AET in the Swedish population, it is also relevant to analyse potential differences between the average treatment effect on the treated and the average treatment effect on the untreated.

[27] In unreported analyses, we also studied the relationship between participating in several types of job-related, non-formal AET, among individuals who participated in at least one such AET type, and found evidence of positive effects of participating in three or all four types (about 7 per cent of the sample), and a smaller and statistically insignificant impact of participating in two types (about 14 per cent of the sample), compared with the baseline category of participating in one type only (about 22 per cent of the sample).

That is, it is useful to compare the expected impact of AET among participants and non-participants. Indeed, as with other types of education, it may be reasonable to assume that individuals expecting larger gains from AET are more likely to participate in and benefit from it than non-participants (see Cornelissen et al. 2016). If this is the case, the expected impact among non-participants may be lower than among participants, which in turn is reflected in the average treatment effect in the population.[28] Depending on the size of any difference, this could be important for policy purposes: if AET mostly benefits current participants, there would be little point in recommending increased take-up among current non-participants.

We therefore analyse the differences between the average treatment effects on the treated and the untreated of AET overall as well as job-related, non-formal AET specifically. We also compare these parameters with the average treatment effect in the population. Table A.4 in the Appendix displays the results from this exercise. While the average treatment effect on the treated is marginally larger than the average treatment effect on the untreated when studying the relationship between employment and AET overall, the absolute difference is small and not statistically significant. This also applies to the difference between these two parameters and the average treatment effect in the population.

Turning to the analysis of job-related, non-formal AET specifically, the difference between the average treatment effects on the treated and the untreated increases somewhat and becomes statistically significant at the 10 per cent level. Yet the average treatment effect on the untreated also remains economically and statistically significant. Meanwhile, the differences between the two parameters and the average treatment effect

[28] The average treatment effect in the population is a weighted average of the average treatment effects on the treated and the untreated (Cornelissen et al. 2016).

in the population, while marginally statistically significant, are small in absolute terms. Overall, the results therefore suggest that also the average treatment effect on the untreated is sizable – and, consequently, that take-up of relevant AET among non-participants may very well raise their employment prospects as well.

6. Conclusion

As rapid technological development increases knowledge requirements in developed countries' labour markets, it is likely to become more important for people to continuously maintain and update their skills to ensure high employment rates in the future. There are thus reasons to believe that adult education and training could play a key role in ensuring well-functioning labour markets in the future.

In this paper, we have analysed how AET is related to employment outcomes in Sweden, exploiting data from the international survey PIAAC, which allows us to obtain rich information on individuals' observable characteristics, including cognitive skills, formal education levels, and work history in the year prior to the survey. In combination with our exploiting an inverse-probability weighted regression-adjustment estimator, this increases the probability that our methodology overcomes bias arising from individual selection into AET. We found that individuals who participated in AET in the year prior to the survey are about 4 percentage points more likely to do paid work in the week before the survey than comparable individuals who did not undergo AET. Intriguingly, the relationship is entirely driven by job-related AET – and this is in turn entirely driven by non-formal, job-related AET. We further found that the relationship is very similar across different types of non-formal, job-related AET. And while we found some evidence that the expected impact on participants of non-formal, job-related AET is slightly larger than the expected impact on non-participants, the latter is considerable as well.

We further found that the positive relationship between AET and employment if anything is even larger when analysing the probability of working full time instead of the probability of doing any paid work at all. Interestingly, the relationship between non-formal, job-related AET and employment also appears to be 'dose dependent', as it increases with the number of such AET activities in which individuals participated. Yet non-formal, non job-related AET and formal AET of either type are not related to the employment outcomes under investigation.

Due to data availability and methodology, we are unable to conclusively rule out omitted-variable bias. We cannot therefore with certainty claim that the results reflect the true causal impact of AET on the probability of employment. Nevertheless, given the paucity of research analysing the effects of different types of AET on employment outcomes, we believe the paper still provides an important contribution to understanding of the relationship between AET and employment.

Also, of course, by adjusting for work history in the year prior to the survey, our analysis effectively focuses on the employment effects of AET among people who did paid work in the same period as they participated, or did not participate, in lifelong learning. In other words, the study is silent on the effectiveness of AET among the unemployed and people outside the labour force. Future research should seek to analyse the impact of AET in this group of people specifically.

Similarly, it is important to consider the context of our findings: we analyse data collected in Sweden during the country's economic recovery following the 2008 financial crisis. Since the effects of AET on employment outcomes may well be country specific and interact with the business cycle, future research should investigate the generalisability of the results in these respects.[29] Also, it would be useful to analyse the extent to which the effects of AET differ across countries. Nevertheless, the positive relationship found in a developed country in the aftermath of a serious economic downturn at least suggests that adult education and training could play a role in ameliorating negative employment effects in similar settings.

Overall, our findings indicate that policies seeking to increase take-up of non-formal, job-related AET and increase incentives among employers to offer AET to their employees may be useful. Further research into the extent to which these findings reflect a causal relationship is nevertheless necessary. And while reforms to increase access to lifelong learning should be considered, more research into what works in this respect is necessary before deciding on such reforms on a large scale. Finding out what works to efficiently raise relevant AET take-up is thus likely to be a fruitful venue of future research.

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[29] Still, it is worth noting that prior research analysing data from other countries, which have very different labour markets compared with Sweden, does often suggest that training is positive for labour-market outcomes (see, for example, Dearden et al. 2006; Lynch 1992; Pischke 2001). This would support the idea that the relationship found in this paper may well be generalisable to other countries and contexts.

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Tables

Table 1: AET and the probability of doing paid work

	OLS	OLS	OLS	IPWRA	IPWRA	IPWRA
	(1)	(2)	(3)	(4)	(5)	(6)
AET	0.18***	0.14***	0.05***	0.17***	0.13***	0.04***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Background variables	Yes	Yes	Yes	Yes	Yes	Yes
Education and PIAAC scores	No	Yes	Yes	No	Yes	Yes
Paid work in the previous year	No	No	Yes	No	No	Yes
Never done paid work	No	No	Yes	No	No	Yes
R^2	0.08	0.12	0.48	N/A	N/A	N/A
n			3,884			

Note: Significance levels: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parentheses. We always restrict the sample to observations that do not violate the overlap assumption in Column 6.

Table 2: Balance tests on covariates

	Standardised differences		Variance ratio	
	Raw	Weighted	Raw	Weighted
PIAAC numeracy score	0.50	-0.02	0.74	1.03
PIAAC literacy score	0.58	-0.02	0.75	1.04
First-generation immigrant	-0.13	-0.02	0.79	0.96
Missing dummy for immigrant background	0.05	-0.01	1.18	0.98
Second-generation immigrant	-0.02	0.02	0.90	1.13
Years in Sweden	-0.22	0.03	0.77	1.02
Mother's education	0.38	-0.04	1.34	0.99
Missing dummy for mother's education	-0.10	0.00	0.52	1.01
Father's education	0.34	-0.01	1.34	1.04
Missing dummy for father's education	-0.16	-0.01	0.48	0.95
Books at home	0.46	-0.02	0.90	0.91
Missing dummy for books at home	-0.10	0.00	0.17	0.94
Years of schooling	0.59	-0.01	0.93	1.16
Age	-0.44	0.03	0.92	0.99
Gender	0.09	-0.03	1.01	1.00
Paid work in the previous year	0.49	0.01	0.35	0.97
No paid work ever	-0.07	-0.01	0.62	0.92
Number of people in household	0.11	-0.02	0.96	0.96
Native language is Swedish	0.11	0.03	0.83	0.96
Test for covariate balance (p-value)		0.94		

Note: the table displays standardised differences between the treatment and control group and the variance ratios for these groups based on the model in Column 6 in Table 1. The raw (weighted) number of observations in the treatment/control group is 2,659/1,225 (1,994.7/1,889.3). All raw differences are statistically significant at least at the 10% level, with the exception of the differences in the following variables: “Missing dummy for immigrant background”, “Second-generation immigrant”, and “No paid work ever”.

Table 3: Effects of different types of AET on the probability of doing paid work

Panel 1	(1)
Job-related AET	0.06***
	(0.01)
Non job-related AET	0.01
	(0.02)
Differences between AET categories (p-value)	
Job-related AET = Non job-related AET	<0.01
n	3,872
Panel 2	**(2)**
Job-related, formal AET	-0.01
	(0.03)
Non job-related, formal AET	-0.09
	(0.07)
Job-related, non-formal AET	0.08***
	(0.01)
Non job-related, non-formal AET	0.02
	(0.02)
Differences between AET categories (p-value)	
Job-related, non-formal AET = Job-related, formal AET	<0.01
Job-related, non-formal AET = Non job-related, formal AET	0.01
Job-related, non-formal AET = Non job-related, non-formal AET	0.01
n	3,858
Panel 3	**(3)**
Job-related, formal AET	-0.01
	(0.03)
Non job-related, formal AET	-0.11
	(0.08)
Non job-related, non-formal AET	0.03
	(0.02)
On-the-job training (job-related, non-formal AET)	0.06***
	(0.02)
Seminars and workshops (job-related, non-formal AET)	0.08***
	(0.02)
Courses through open or distance education (job-related, non-formal AET)	0.09***
	(0.03)
Other courses or private lessons (job-related, non-formal AET)	0.06**
	(0.03)
Differences between job-related, non-formal AET categories (p-value)	
On-the-job training = Seminars and workshop	0.61
On-the-job training = Courses through open or distance education	0.51
On-the-job training = Other courses or private lessons	0.83
Seminars and workshops = Courses through open or distance education	0.79
Seminars and workshops = Other courses or private lessons	0.53
Other courses or private lessons = Courses through open or distance education	0.44
n	2,770

Note: Significance levels: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parentheses. The models include the same covariates as the one presented in Column 6 in Table 1.

Table 4: Robustness tests

	(1)	(2)	(3)	(4)
	Full-time work	People aged 35+	Add industry and region	Only age, gender, and paid work in previous year as covariates
Panel 1				
AET	0.07***	0.06***	0.04***	0.05***
	(0.02)	(0.01)	(0.01)	(0.01)
n	3,883	2,820	3,883	3,890
Panel 2				
Job-related AET	0.10***	0.07***	0.05***	0.06***
	(0.02)	(0.01)	(0.01)	(0.01)
Non job-related AET	-0.03	0.03	0.00	0.01
	(0.03)	(0.02)	(0.02)	(0.02)
n	3,871	2,809	3,847	3,878
Panel 3				
Job-related, formal AET	-0.05	0.04	-0.05	0.02
	(0.04)	(0.03)	(0.03)	(0.05)
Non job-related, formal AET	-0.03	0.01	-0.07	-0.03
	(0.09)	(0.11)	(0.04)	(0.05)
Job-related, non-formal AET	0.12***	0.07***	0.07***	0.08***
	(0.02)	(0.02)	(0.01)	(0.01)
Non job-related, non-formal AET	0.01	0.03	0.02	0.03
	(0.03)	(0.03)	(0.02)	(0.02)
n	3,857	2,749	3,722	3,878

	(5)
Panel 4	Only job-related, non-formal AET compared with no AET
Job-related, non-formal AET	0.08***
	(0.01)
Test for covariate balance (p-value)	0.96
n	2,962

Note: Significance levels: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parentheses.

Table 5: Effects of job-related, non-formal AET by training intensity

	(1)
1 job-related, non-formal activity	0.065***
	(0.018)
2 job-related, non-formal activities	0.070***
	(0.018)
3–5 job-related, non-formal activities	0.074***
	(0.018)
>5 job-related, non-formal activities	0.111***
	(0.015)
<u>Differences between categories (p-value)</u>	
>5 job-related, non-formal activities = 1 job-related, non-formal activity	0.02
>5 job-related, non-formal activities = 2 job-related, non-formal activities	0.05
>5 job-related, non-formal activities = 3–5 job-related, non-formal activities	0.06
3–5 job-related, non-formal activities = 1 job-related, non-formal activity	0.70
3–5 job-related, non-formal activities = 2 job-related, non-formal activities	0.87
2 job-related, non-formal activities = 1 job-related, non-formal activity	0.84
n	3,799

Note: Significance levels: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parentheses. The models include the same covariates as the one presented in Column 6 in Table 1.

Appendix

Table A.1: Descriptive statistics

Variable	Mean	SD	Min	Max
Participated in AET	0.65	0.48	0	1
Participated in AET (paid work in the previous year)	0.70	0.46	0	1
Participated in AET (no paid work in the previous year)	0.37	0.48	0	1
Participated in job-related AET	0.52	0.50	0	1
Participated in non job-related AET	0.13	0.34	0	1
Participated in formal AET	0.14	0.35	0	1
Participated in formal, job-related AET	0.10	0.30	0	1
Participated in formal, non job-related AET	0.04	0.20	0	1
Participated in non-formal AET	0.60	0.49	0	1
Participated in non-formal, job-related AET	0.49	0.50	0	1
Participated in non-formal, non job-related AET	0.11	0.31	0	1
On-the-job training (job related)	0.29	0.45	0	1
Seminars and workshops (job related)	0.28	0.45	0	1
Courses through open or distance education (job related)	0.12	0.32	0	1
Other courses or private lessons (job related)	0.15	0.36	0	1
Number of job-related, non-formal AET activities	2.45	5.31	0	83
1 job-related, non-formal AET activity	0.13	0.33	0	1
2 job-related, non-formal AET activities	0.09	0.28	0	1
3–5 job-related, non-formal AET activities	0.15	0.36	0	1
>5 job-related, non-formal AET activities	0.13	0.33	0	1
Paid work	0.73	0.44	0	1
Full-time work	0.61	0.49	0	1
Paid work in the previous year	0.85	0.35	0	1
No paid work ever	0.02	0.14	0	1
Age	43.53	13.01	16	65
Woman	0.49	0.50	0	1
Number of people in household	2.70	1.32	1	6
First-generation immigrant	0.19	0.39	0	1
Second-generation immigrant	0.03	0.17	0	1
Native language is Swedish	0.89	0.38	0	1
Years in Sweden	39.31	16.36	0	65
Number of books at home	3.79	1.40	1	6
Mother's educational level	1.66	0.82	1	3
Father's educational level	1.69	0.83	1	3
Years of schooling	12.21	2.55	6	20
PIAAC literacy score	278.09	49.04	23.57	415.64
PIAAC numeracy score	278.54	53.35	52.18	444.13

Note: all data are weighted by respondents' sampling probability in PIAAC. Only observations without imputed values are used to calculate the descriptive statistics. The 21 industry and 8 geographical dummies, as well as dummies indicating missing values for covariates, are suppressed.

Table A.2: Results after trimming the sample to increase overlap

Above the 30th and below the 70th percentile of the propensity-score distribution (no AET)	
AET	0.05**
	(0.02)
n	1,552
Above the 30th and below the 70th percentile of the propensity-score distribution (no AET)	
Job-related AET	0.07***
	(0.02)
Non job-related AET	0.02
	(0.02)
n	1,551
Below the 40th percentile of the propensity-score distribution (no AET)	
Job-related, formal AET	0.00
	(0.04)
Non job-related, formal AET	-0.02
	(0.06)
Job-related, non-formal AET	0.08***
	(0.03)
Non job-related, non-formal AET	0.02
	(0.04)
n	1,503

Note: Significance levels: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parentheses.

Table A.3: The main results when utilising alternative estimators

	IPWRA	Propensity-score matching	Entropy balancing	IPWRA	Propensity-score matching	Entropy balancing
AET	0.04***	0.06***	0.04**			
	(0.01)	(0.02)	(0.02)			
Job-related, non-formal AET				0.08***	0.08***	0.07***
				(0.01)	(0.02)	(0.02)
n	3,884	3,884	3,884	2,962	2,962	2,962

Note: Significance levels: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parentheses. All models include the same control variables as Column 6 in Table 1. Columns 4–6 excludes respondents who have undergone different types of AET than job-related, non-formal AET only. The propensity-score matching estimator uses one match per observation. The entropy balancing estimator reweights the data to ensure that the treatment and control groups are exactly balanced in terms of means, variances, and skewness of the covariates. Note that the matching and entropy balancing estimators do not incorporate the population weights, which by definition also generates slight differences compared with IPWRA.

Table A.4: average treatment effect in the population, on the treated, and on the untreated

	ATE	ATT	ATU	ATE	ATT	ATU
AET	0.04***	0.05***	0.04***			
	(0.01)	(0.02)	(0.01)			
Job-related, non-formal AET				0.08***	0.09***	0.06***
				(0.01)	(0.02)	(0.01)
ATT = ATU		0.24			0.05	
ATT = ATE		0.24			0.05	
ATU = ATE		0.24			0.05	
n		3,884			2,962	

Note: Significance levels: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parentheses. All models include the same control variables as Column 6 in Table 1. Columns 4–6 excludes respondents who have undergone different types of AET than job-related, non-formal AET only. ATE= Average Treatment Effect. ATT = Average Treatment Effect on the Treated. ATU = Average Treatment Effect on the Untreated.

Figure A.1: Overlap plots (AET)

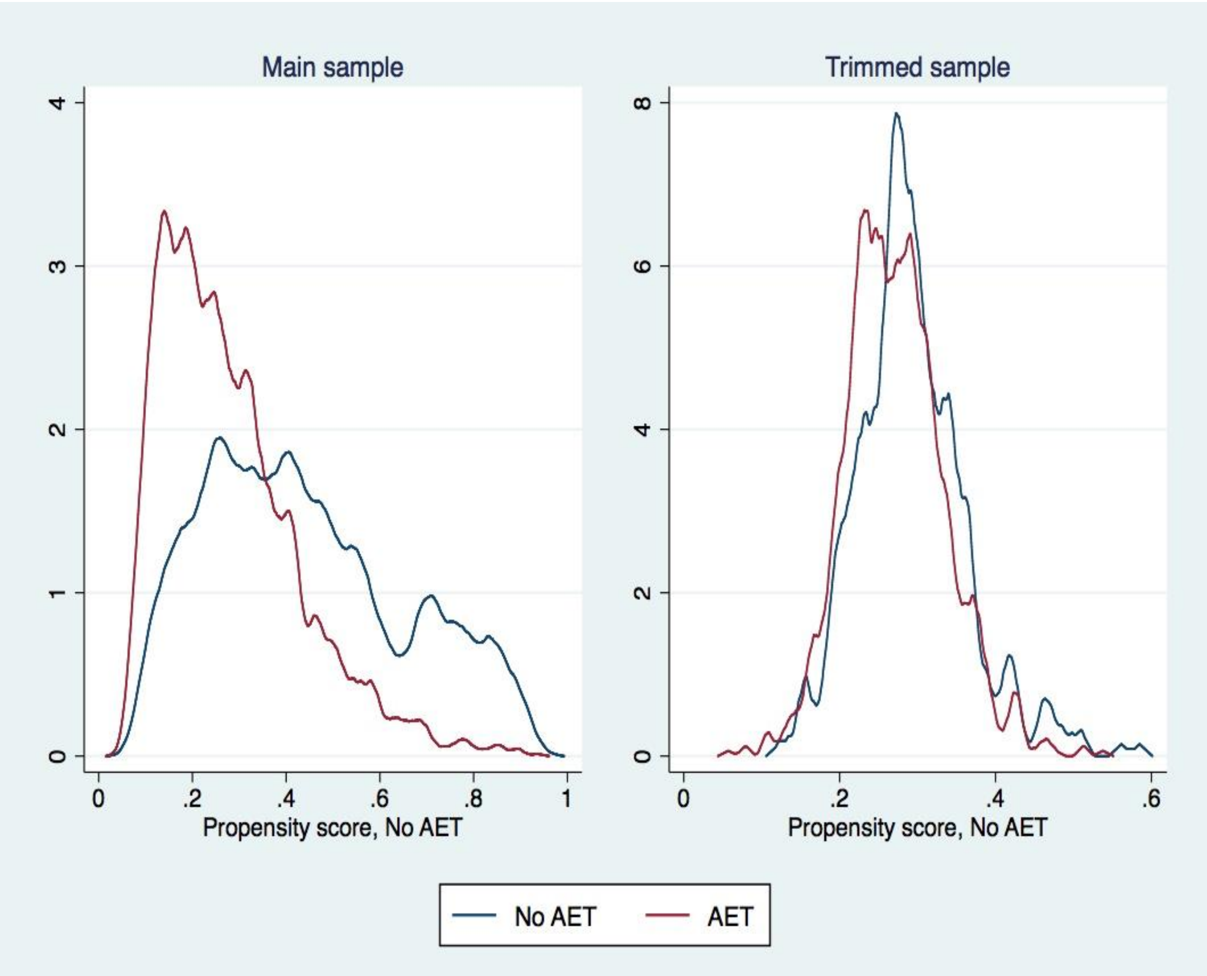


Figure A.2: Overlap plots (Job-related & non job-related AET)

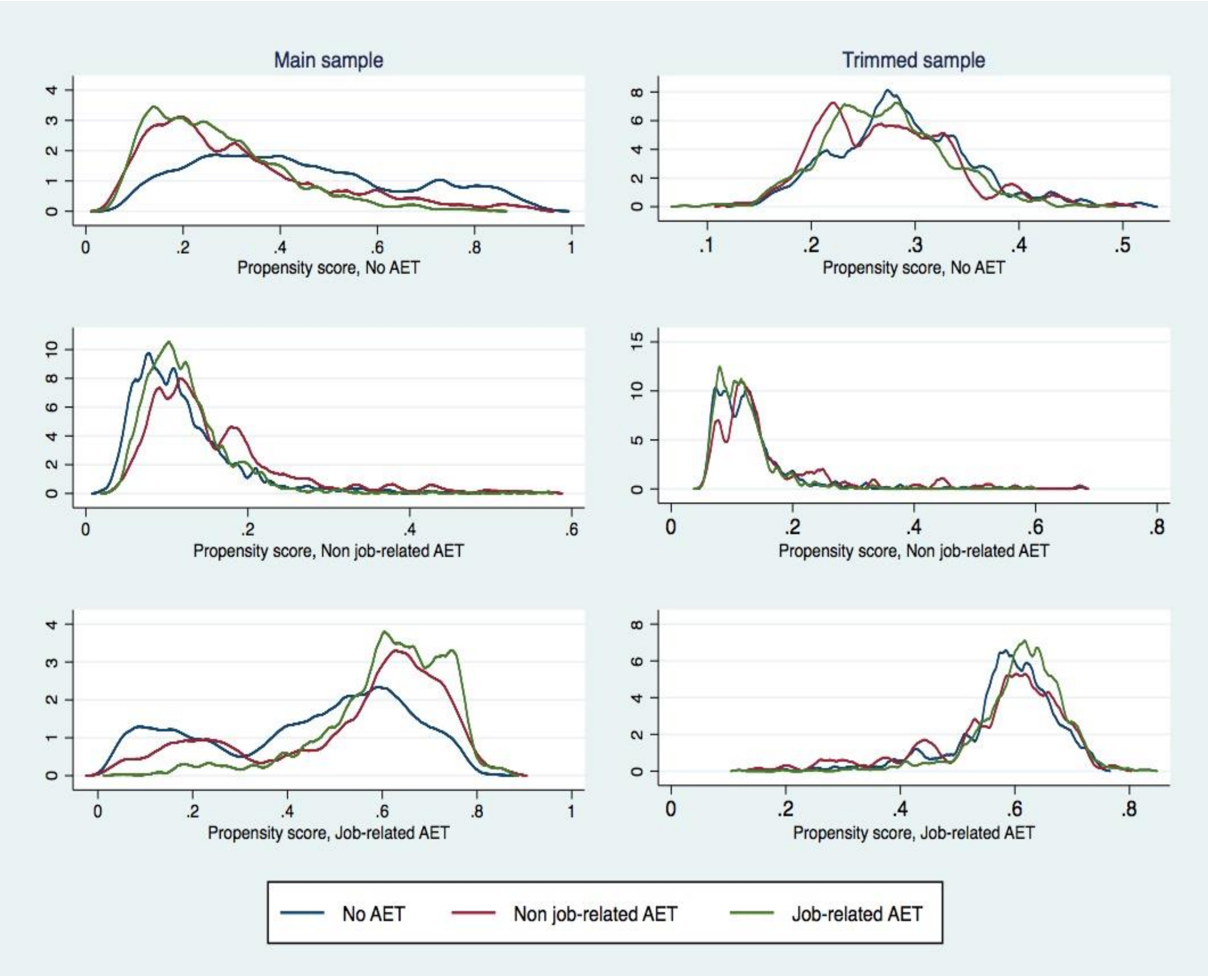


Figure A.3: Overlap plots (Job-related/non job-related & formal/non-formal AET)

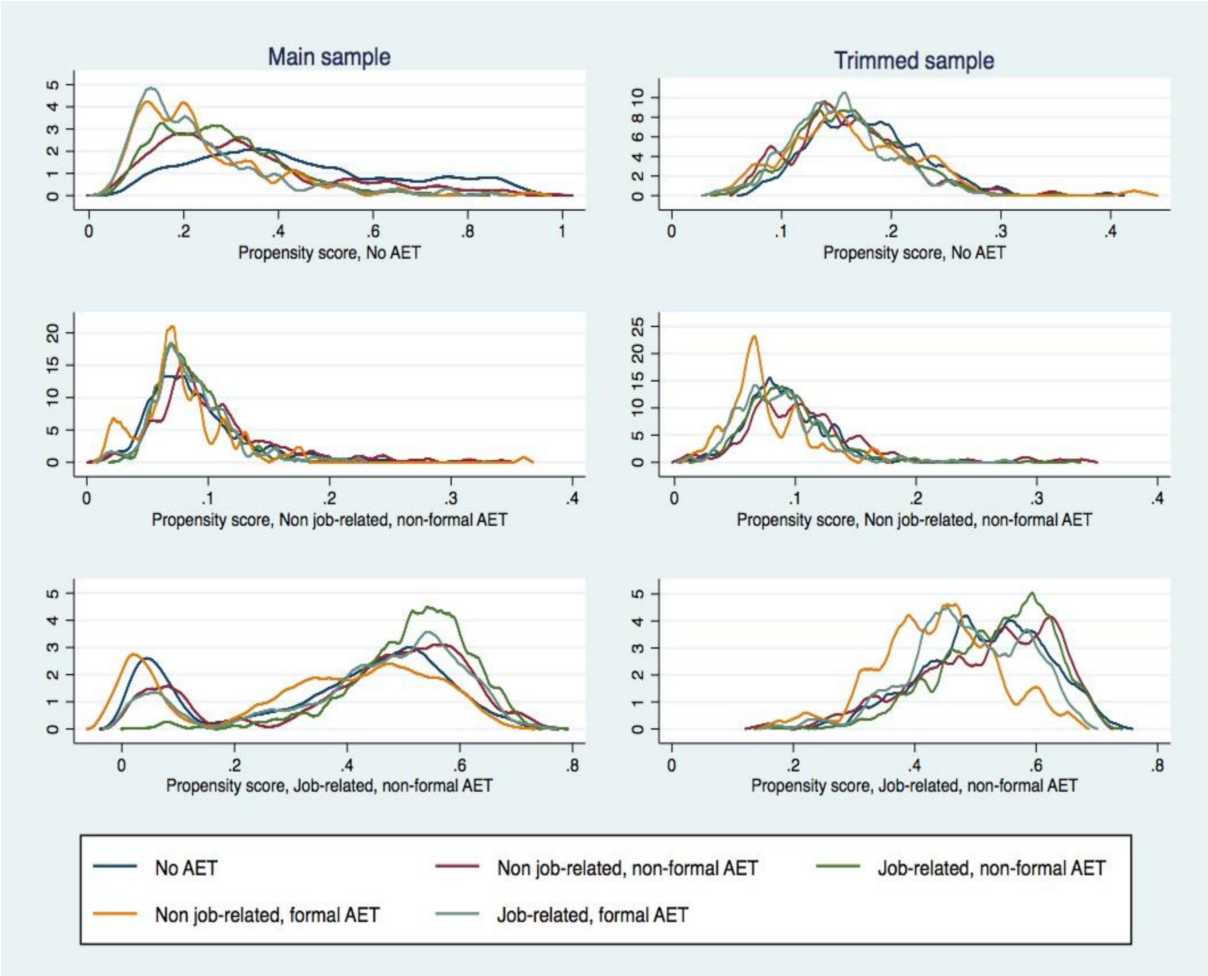
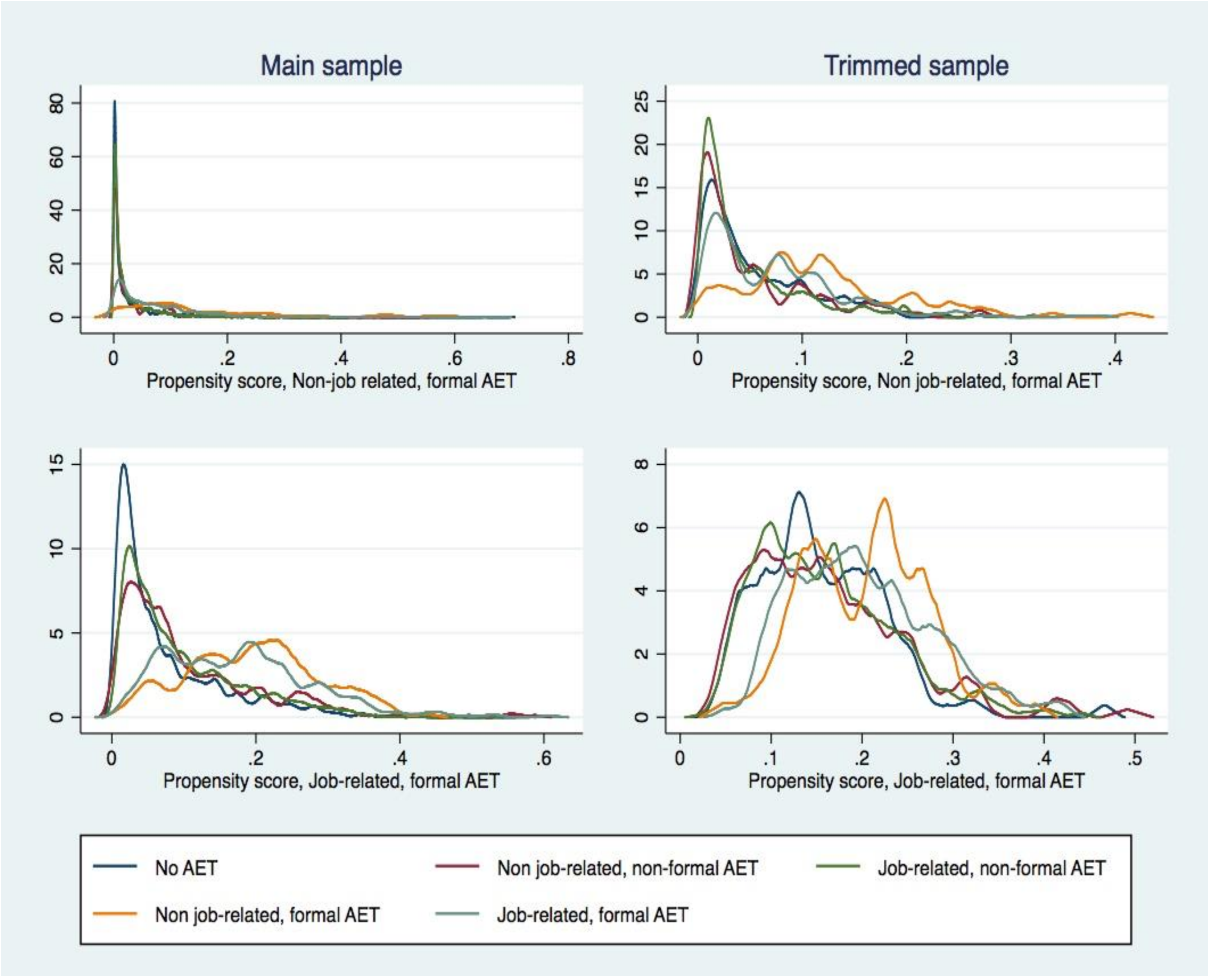


Figure A.4: Overlap plots (Job-related/non job-related & formal/non-formal AET)



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Disclosure statement

No conflict of interest.