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"The Double Dividend of Training" − Labor Market Effects of Work-Related Continuous Education in Switzerland

Abstract

This paper presents the first longitudinal estimates of the effect of work-related training on labor market outcomes in Switzerland. Using a novel dataset that links official census data on adult education to longitudinal register data on labor market outcomes, we apply a regression-adjusted matched difference-in-differences approach with entropy balancing to account for selection bias and sorting on gains. We find that training participation increases yearly earnings and reduces the risk of unemployment two years after the treatment. However, the effects are heterogeneous as to gender, age, education, and regional labor market context. The gains are highest for middle-aged men with formal vocational education working in either depressed or booming labor markets.

JEL-Codes: I210, I260, J240, M530.

Keywords: continuous education, wages, unemployment, entropy balancing, Switzerland.

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1. Introduction

Adult education has become a crucial factor for aging economies to maintain and improve workers' skills and knowledge and to prevent human capital depreciation. Thus, participation in lifelong learning activities has become widespread in many OECD countries. On average, 40 percent of 25- to 64-year-olds participate in nonformal education activities (OECD, 2017). While there is an ongoing interest in and a relatively large body of literature on the effects of adult education on labor market outcomes, the evidence is far from complete. For example, in a recent survey of the literature, Midtsundstad (2019) concludes that there is only scarce evidence on the effect of adult education on employment and that it is highly questionable whether the results from the literature can be generalized to countries with different educational systems, different average levels of education, different labor markets (regulations) and welfare states.

In this paper, we address some of these limitations by studying the labor market effects of continuing education and training (CET) in Switzerland. We are interested not only in earnings effects but also in whether CET affects the risk of becoming unemployed. Switzerland is particularly interesting because Switzerland had the highest share (58 percent) of 25- to 64-year-olds who participated in job-related nonformal education and training among all European countries participating in the Adult Education Survey (AES) in 2016.[1] For comparison, the average across all European countries was only 35.3 percent. Moreover, the Swiss labor market can be characterized as liberal, and adult education is—in contrast to most other countries with high participation rates—privately organized.[2] Because the current literature focuses mainly on training effects in more regulated labor markets and with publicly provided or organized adult education (Midtsundstad, 2019), Switzerland provides a unique setting in which to show whether the effects found in the literature thus far can be generalized.[3]

This study is possible because we were able to combine three different administrative datasets. The information on training participation comes from the microcensus on education and training of the Swiss Federal Statistical Office (SFSO) in 2016. The survey defined continuous education and training (CET) as all learning activities with a work-related purpose that took place in nonformal courses within the 12 months prior to the survey. According to these data, 66 percent participated in work-related nonformal training, with on average of 2.6 (median: 2) training courses. The duration of the training was 54 hours on average (median: 26 hours), and most participants (77 percent) had their training financed by their employer. These census data are matched to longitudinal administrative data on income and labor market participation from the social insurance statistics and to the administrative data of unemployment insurance for the years 2014 to 2018.

[1] Cf. Eurostat: Adult Education Survey, 2016:
https://ec.europa.eu/eurostat/databrowser/view/trng_aes_121/default/table?lang=en

[2] According to the OECD Employment Outlook 2019, Switzerland ranks among the countries with low regulatory protection (OECD, 2020), and in the annual report of the Fraser Institute on the economic freedom of the world, it ranks within the first quartile, taking fourth place (Gwartney, 2020). Moreover, adult education in Switzerland is mainly privately organized, and expenses are generally borne by employers or participants (SCCRE, 2018).

[3] This study also adds to only two older studies that have looked into the effects of CET on labor market outcomes in Switzerland (Gerfin, 2004; Schwerdt, Messer, Woessmann, & Wolter, 2012). While the first relied on an IV approach to estimate causal effects, the second studied the effects in the context of an RCT with vouchers for CET.

With these data, we are able to show that work-related training yields positive labor market outcomes in Switzerland. Our results show that participation in training increases yearly earnings by 5.1 percent compared to that of nonparticipants, which is comparable to similar studies in the literature (see Section 2). Moreover, we document that training reduces the risk of becoming unemployed by 2.8 percentage points. Thus, training participation provides a double dividend by increasing earnings and stabilizing employment.

These results are obtained by comparing labor market outcomes before and after participation in training and between participants and nonparticipants. Because a simple comparison would lead to biased results due to self-selection into the treatment, we use a regression-adjusted matched difference-in-differences framework (Heckman, Ichimura, & Todd, 1997, 1998; Smith & Todd, 2005a, 2005b; Todd, 2008) to establish identification. This approach allows us to control for selection into the treatment on time-invariant unobserved heterogeneity. To further facilitate the common trend assumption of identical trends in the treatment and comparison groups in the absence of the treatment, which is required for giving our estimates a causal interpretation, we account for selection on observables in both levels *and* trends (selection on gains) for a larger set of predetermined outcomes and covariates. We use entropy balancing to construct matching weights (Hainmueller, 2012). The approach calibrates unit weights in the comparison group such that covariates of the reweighted comparison group satisfy prespecified balancing conditions. In our application, we demand that the comparison group matches the treatment group in terms of income and unemployment two years prior to the treatment, as well as full-time employment, education, occupation, gender, age, marital status, children, citizenship status, and region of residence. Compared to conventional propensity score matching, the approach has several advantages. First, entropy balancing allows us to match not only average covariates but also the variance of the covariates. This is meaningful because the training participants are a more homogenous segment of the population than the comparison group. Second, the nonparametric nature of entropy balancing requires far fewer modeling assumptions than propensity score matching. Third, we do not have to check balancing after matching (as in propensity score matching) because entropy balancing achieves balanced matches by construction.

Our paper further contributes to the literature by documenting an age pattern in the returns on adult education. The results show no effect on earnings and unemployment for younger workers in the age group between 20 and 29 years, whereas the earnings effect is maximized for prime age workers between 30 and 49 years. Concerning employment stability, however, it is the older age group of workers between 45 and 55 years who profit the most from training in terms of unemployment reduction. This age pattern indicates that training seems to be important to prevent skill depreciation and job loss at older working ages. Together with the finding that there are strong positive training effects for workers with a basic vocational education, this suggests that training can be a successful strategy to mitigate adverse effects in the later stages of working life for these workers compared to workers who followed general education programs (Hanushek, Schwerdt, Woessmann, & Zhang, 2017).

A second important effect heterogeneity derives from the sample splits according to the regional labor market context. Assessing the functioning of the labor market by the regional employment rate and the regional unemployment rate, we find that workers profit from training most in very well (high employment rate and low unemployment rate) or in very badly functioning (low employment rate and high unemployment rate) labor markets.

The paper proceeds as follows. Section 2 discusses the related literature. Section 3 introduces the data sources and explains the construction of the dataset and all variables, provides details of the analytical sample, and shows the descriptive statistics. Section 4 describes the empirical setup and the implementation of the estimator. Section 5 presents the results. Section 6 discusses effect heterogeneity regarding individual characteristics and the labor market context. Section 7 concludes the paper.

2. Literature

The literature on the returns of adult education studies covers very different forms of learning activities. First, there are differences in relation to the scope of activities. There are studies on the returns of continuous education and training that define adult education or continuous education very broadly to cover almost any kind of adult learning activity (Blanden, Buscha, Sturgis, & Urwin, 2012; Büchel & Pannenberg, 2004; Dieckhoff, 2007; Ehlert, 2017; Görlitz & Tamm, 2016; Hidalgo, Oosterbeek, & Webbink, 2014; Muehler, Beckmann, & Schauenberg, 2007; Novella, Rucci, Vazquez, & Kaplan, 2018; Schwerdt et al., 2012). Other studies restrict continuous or adult education to work-related training, defined as training activities or courses for the purpose of advancing work and career prospects. These training activities are either worker-financed or financed—fully or only partially—by the employer (Gerfin, 2004; Ruhose, Thomsen, & Weilage, 2019). Finally, there is on-the-job training, which is initiated, organized, and financed entirely by the employer (Görlitz, 2011; Goux & Maurin, 2000; Leuven & Oosterbeek, 2008).

Second, adult education can differ by level of formal education and cover qualifications at either the secondary or tertiary level of the education system. These learning activities usually take place at schools or colleges and serve the purpose of catching up on missed educational qualifications in adolescence or early adulthood. This type of adult education is quite common in Scandinavian countries, where many different programs to promote adult education exist to make up for above average dropout rates from formal education in adolescence. These programs are therefore targeted at people with labor market experience without formal qualifications at the upper-secondary or tertiary level. There are also specific training and vocational education programs leading to higher vocational qualifications. Because these programs aimed to obtain formal qualifications at the postcompulsory education level are usually very time intensive, the participants do not benefit from free tuition but very often receive extra allowances to cover their living costs (Böckerman, Haapanen, & Jepsen, 2019; Dorsett, Lui, & Weale, 2016; Kauhanen & Antti, 2018; Stenberg, Luna, & Westerlund, 2012; Stenberg & Westerlund, 2015; Stevens, Kurlaender, & Grosz, 2019).

Third, there are specific training programs to help unemployed people find a job. This type of adult education has traditionally been well covered empirically in studies that evaluate active labor market policies (Bernhard & Kruppe, 2012; Crépon, Ferracci, & Fougère, 2012; Doerr, Fitzenberger, Kruppe, Paul, & Strittmatter, 2017; Gerfin & Lechner, 2002; Hujer, Maurer, & Wellner, 1999; Lechner & Wunsch, 2009).

The main empirical challenge of most of these studies is to deal with the self-selection of individuals into adult education. Most of the earlier studies used panel models with individual fixed effects to control for unobservable heterogeneity that is assumed to be constant over time (Blanden et al., 2012; Büchel & Pannenberg, 2004; Ehlert, 2017; Goux & Maurin, 2000; Lechner, 1999; Pischke, 2001). In addition, studies have used panel models with individual-specific linear time trends to control for individual trends in labor market outcomes (Büchel & Pannenberg, 2004). Other studies used detailed register data with employer-specific information (worker–firm matched data) to control for firm-specific compensation (Goux & Maurin, 2000).

Earlier but also more recent studies tried to provide evidence on the effect of adult education based on observational data in combination with econometric estimation techniques to construct a suitable comparison group for training participants. This part of the literature has extensively studied the combination of difference-in-differences estimators with propensity score matching (Dehejia & Wahba, 2002; see, e.g., Heckman et al., 1997, 1998; Smith & Todd, 2005a, 2005b; Todd, 2008). Muehler et al. (2007) and Novella et al. (2018) provide some examples for early and more recent applications of this method. Most recently, and closest to this paper, Ruhose et al. (2019, 2020) used entropy balancing (Hainmueller, 2012) instead of propensity score matching for the construction of the comparison group for evaluation of monetary and nonmonetary returns to work-related training in Germany.

Arguably, a more credible source of identifying variation comes from (quasi-)experiments. For example, studies have used randomized control trials to study the effectiveness of specific training programs (see, e.g., LaLonde, 1986). Other experiments exploit the variation of a random allocation of training vouchers implemented on a wider scale (Görlitz & Tamm, 2016; Schwerdt et al., 2012). However, experimental results, which are mainly based on a random assignment of training vouchers, usually do not show average treatment effects on the treated (ATT) because voucher take-up is not random. The studies therefore causally identify an intention-to-treat effect (ITT) instead. Furthermore, the use of experiments is limited to certain interventions and treatment groups and can therefore not answer every socially relevant question.

Finally, some studies constructed a control group that was composed of individuals who, for instance, planned to participate in training but did not due to random events such as illness or cancellation of the course (Gerfin, 2004; Görlitz, 2011; Leuven & Oosterbeek, 2008).

The results from the nonexperimental (and some experimental) studies suggest that training participation raises earnings between 3 and 12 percent (LaLonde, 1986; Muehler et al., 2007; Novella et al., 2018; Pischke, 2001; Ruhose et al., 2019; Vignoles, Galindo-Rueda, & Feinstein, 2004). The observed effects are heterogeneous, depending, e.g., on gender (Blanden et al., 2012), age (Büchel & Pannenberg, 2004), type of training or industry sector (Ehlert, 2017). In contrast, most experimental studies using arguably exogenous events in nonparticipation and randomly allocated training vouchers conclude that there are no causal effects from participation in training (Görlitz, 2011; Görlitz & Tamm, 2016; Leuven & Oosterbeek, 2008, Schwerdt et al., 2012), although some of these studies cover only short-term effects. Furthermore, while the experimental literature can provide credible evidence on the causal returns of adult education, the effects are often limited to the very specific circumstances of the experiment (e.g., the up-take of a voucher), and therefore, generalizability to a broader population is often not possible. Thus, to gain insights into the relationship between training participation and economic outcomes for a broader adult population, we still must rely on quasi-experimental techniques with observational data.

While the earnings effects of training participation are extensively studied, there is much less evidence on the relationship between training participation and unemployment (Midtsundstad, 2019). If at all, employment effects are often studied in the context of active labor market evaluation programs. Most of this work finds no effects and even sometimes negative effects in the short run (Bernhard & Kruppe, 2012; Gerfin & Lechner, 2002; Görlitz, 2011; Görlitz & Tamm, 2016; Hujer et al., 1999; Lechner & Wunsch, 2009).

3. Data

This section provides information on how the different administrative data records have been merged and what data the analytical sample contains to study the relationship between training participation and labor market outcomes such as earnings and unemployment in Switzerland.

3.1. Data sources

The main data source for adult education activities in Switzerland is the official Swiss Microcensus on Education and Training (MET) from 2016.[4] The MET provides information on the educational activities of the Swiss population, restricted to the permanent resident population between 15 and 74 years of age. The sample includes information from over 11,000 individuals. The data cover sociodemographic characteristics, current educational and training activities, and the reasons for participating in education and learning programs. The MET was conducted between April and December 2016, and it covers training from April 2015 until December 2016 (see Figure 1).[5]

The earnings data were matched for all respondents in MET. The earnings data were provided by the Central Compensation Office (CCO). The CCO is the federal institution that implements the central pillars of the social security system (old-age pensions, disability insurance and compensation for loss of earnings). Their register data comprise the total yearly gross income from paid employment (excluding income from self-employment for all insured people who are subject to social security contributions). We use the information from 2014 to 2018 (see Figure 1).[6] Since the earnings data cover in principle all individuals surveyed in the MET, we were able to match earnings information to almost all of them (99.1 percent).

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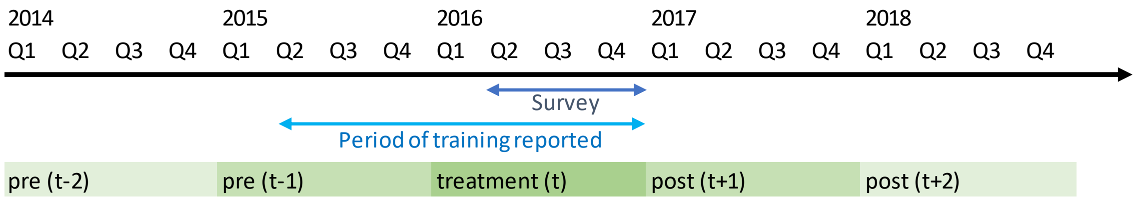
[4] The MET is carried out in a five-year interval. The data collection is done by computer-assisted telephone interview (CATI).

[5] Since some of the survey was conducted at the beginning of 2016, there are individuals who also include 2015 CET activities in their response. Since the matching includes information from 2014 and 2015, our effect estimates are rather conservative and may underestimate the true labor market effects of CET.

[6] Overall, the total sample contained 44,485 income observations for the 11,509 individuals present in the MET sample.

Figure 1: Timing of surveys



Notes: The figure shows the timing of the Swiss Microcensus on Education and Training (MET) from 2016 and the available information on earnings and unemployment two years before and two years after the training periods.

An important limitation of this data source is that it provides us with information on only yearly income. Thus, we do not observe the hours worked, which prevents us from decomposing the effect of training participation into changes in hourly compensation and changes along the labor supply margin. The only information on the labor supply margin that we have is the information on whether the individual is employed full-time (i.e., working more than 37.8 hours per week) or part-time. This information comes from the MET and is available for 2016 only.

The third source of information is the register data on unemployment. These data are collected by the national unemployment insurance office and provided to us by the State Secretariat for Economic Affairs (SECO). The register data contain information on the unemployment status of the entire population and list the monthly unemployment periods, which we aggregated into yearly unemployment information that we could merge with the MET.[7]

3.2. Variables

In the context of this study, we define continuous education and training (CET) as all learning activities with a work-related purpose that takes place in nonformal courses. The treatment variable takes the value of 1 if the respondent has participated in such work-related training within the past 12 months and 0 if the respondent has not participated in CET during that period.

Our main outcome variables are the earnings and unemployment status of the individual. To assess the effect of CET on earnings, we mainly use the log yearly earnings in 2017 and 2018, i.e., one and two years after CET participation. For unemployment, we use the information in the official register for people currently not employed, seeking a job and able to immediately start a new job.

To construct our comparison group, we use a set of conditioning variables that are known to affect participation in training as well as labor market outcomes (see Table 1). They cover outcomes before treatment (such as earnings and unemployment experience), demographic char-

[7] In total, we could match information on unemployment periods from the SECO data to 593 individuals included in the MET sample. This represents a total of 2,947 observations, or in other words, we observe for 5.4 percent of the sample at least one unemployment period in the two years following the treatment.

acteristics (such as gender, age, marital status, children, citizenship status, and region of residence), education (five categories), and occupation (six categories). The next section provides more detail about how we use them to construct the comparison group.

3.3. Analytical sample and descriptive statistics

For our analysis, we restrict the sample to people aged between 20 and 60 years and for whom we have complete earnings data.[8] Thus, our analytical sample, which includes observations with valid information on all control variables, comprises a total of 29,062 person-year observations with 5,860 unique persons (see Appendix Table A.2 for an overview of the sample construction).[9] Within the sample, we count 20,777 person-year observations (4,179 persons) for the group of training participants and 8,285 person-year observations (1,681 persons) for the group of nonparticipants.[10]

Table 1 reports the descriptive statistics separately for the training participants and nonparticipants. On average, 71 percent of the sample reported participation in work-related nonformal training within the 12 months before the survey. The course participation is distributed as follows. The average number of training courses is 2.6 (median: 2). On average, individuals participated in training courses for 54 hours (median: 26 hours). A large majority of the participants (77 percent) received training financed by their employer.

The table also reveals that training participants are—not surprisingly, given the large share of employer financing—a positively selected group in general, which corresponds to most of the findings in the related literature. For example, we find a statistically highly significant earnings difference between the training participants and the comparison group of approximately 24,000 Swiss francs already in 2015, before the treatment. We also find that training participants are less likely to be unemployed than nonparticipants before the treatment. This aligns well with the observation that university graduates are much more likely to participate in work-related training (74 percent) than workers with vocational education at the secondary level (48 percent).

[8] Specifically, this means we have dropped individuals who report participation in nonwork-related training (496 persons).
[9] The full sample comprises 31,486 person-year observations. Thus, our analytical sample contains 92 percent of the entire sample.
[10] The share of active people in CET is higher than in the statistics mentioned earlier in this paper because in our analytical sample, we restrict ourselves to people in gainful employment in the year of the census (2016) and not the total of the adult population.

Table 1: Descriptive statistics

Variable	Label	Full sample	Training participants	Comparison group	
		Average	Average	Difference to (4)	p value of (5)
(1)	(2)	(3)	(4)	(5)	(6)
Training characteristics					
Participation in work-related training	0=no; 1=yes	0.71	1.00	–	–
Number of training courses	Average/median	–	2.6/2.0	–	–
Number of training hours	Average/median	–	54/26	–	–
Training financed by employer	0=no; 1=yes	–	0.77	–	–
Labor market characteristics					
Log yearly income (average)	In 2014 Swiss francs	10.957	11.124	-0.449	0.000
Log yearly income, 2014 (c)	In 2014 Swiss francs	10.886	11.049	0.425	0.000
Log yearly income, 2015 (c)	In 2014 Swiss francs	10.949	11.119	-0.448	0.000
Log yearly income, 2016	In 2014 Swiss francs	10.968	11.144	-0.466	0.000
Log yearly income, 2017	In 2014 Swiss francs	11.000	11.158	-0.440	0.000
Log yearly income, 2018	In 2014 Swiss francs	11.012	11.162	-0.431	0.000
Unemployed (average)	0=no; 1=yes	0.069	0.056	0.042	0.000
Unemployed, 2014 (c)	0=no; 1=yes	0.060	0.051	0.032	0.000
Unemployed, 2015 (c)	0=no; 1=yes	0.065	0.055	0.033	0.000
Unemployed, 2016	0=no; 1=yes	0.072	0.058	0.043	0.000
Unemployed, 2017	0=no; 1=yes	0.074	0.058	0.054	0.000
Unemployed, 2018	0=no; 1=yes	0.070	0.054	0.050	0.000
Full-time employed (c)	0=no; 1=yes	0.574	0.603	-0.058	0.000
Demographic characteristics					
Female (c)	0=male; 1=female	0.499	0.480	0.040	0.000
Age (c)		41.611	41.743	0.374	0.009
Married (c)	0=no; 1=yes	0.562	0.562	0.023	0.000
Children (c)	0=no; 1=yes	0.355	0.361	-0.018	0.005
Swiss citizen (c)	0=no; 1=yes	0.795	0.823	-0.112	0.000
Federal state (c)(#)	24 categories	13.560	13.605	0.010	0.922
Education					
Compulsory schooling (c)	0=no; 1=yes	0.091	0.050	0.151	0.000
Upper secondary: vocational (c)	0=no; 1=yes	0.413	0.372	0.130	0.000
Upper secondary: general (c)	0=no; 1=yes	0.110	0.100	0.016	0.000
Tertiary education: vocational (c)	0=no; 1=yes	0.151	0.186	-0.110	0.000
Tertiary education: university (c)	0=no; 1=yes	0.235	0.292	-0.186	0.000
Occupational classification					
Management/judicial authorities (c)	0=no; 1=yes	0.118	0.141	-0.069	0.000
Scientists (c)	0=no; 1=yes	0.186	0.231	-0.133	0.000
Technicians/professionals (c)	0=no; 1=yes	0.241	0.282	-0.127	0.000
Commercial employees (c)	0=no; 1=yes	0.087	0.073	0.040	0.000
Sales/services	0=no; 1=yes	0.127	0.106	0.063	0.000
Craftsmen/workers (c)	0=no; 1=yes	0.099	0.074	0.082	0.000
Unskilled workers (c)	0=no; 1=yes	0.078	0.051	0.092	0.000

Notes: The table shows the descriptive statistics of the main variables. We used a simple t test to test for the significance of the difference between the training participants and the comparison group. (c) indicates variables that are used as conditioning variables. (#) Descriptive statistics by federal state are shown in Appendix Table A.1. Variables refer to the year 2015 unless noted otherwise.
Data sources: Swiss Microcensus on Education and Training (MET), Central Compensation Office (CCO), State Secretariat for Economic Affairs (SECO).

4. Empirical strategy

Given the positive selection into training activities documented in our data, conventional OLS estimates would be upward biased and overestimate the effects of CET (Ashenfelter, 1978; Ashenfelter & Card, 1985; LaLonde, 1986). Therefore, as described in Section 2, several approaches exist that try to construct a comparison group that enables a more meaningful comparison. Because we do not observe any experimentally induced variation in participation in CET and in light of the limitations of experimental approaches (see Section 2 again), we rely on a matching difference-in-differences approach, which of all nonexperimental estimators should work best (see, e.g., Heckman et al., 1997, 1998; Smith & Todd, 2005b; Todd, 2008).

In what follows, we focus on the implementation of a regression-adjusted difference-in-differences matching approach to estimate an ATT, i.e., the training-induced change in earnings and unemployment of those individuals who participated in work-related training (treatment group). Equation (1) describes the estimator. In this setting, n_1 is the number of treated individuals, and group membership is indicated by I_1 (treated) and I_0 (comparison), respectively. The counterfactual comparison group is a weighted average of the change in outcome variables, with weights equal to $w(i,j)$. Y_0^{after} and Y_0^{before} referring to potential outcomes from before and after the treatment in the absence of treatment. Y_1^{after} describes the potential outcome after the treatment for the treatment group.

$$(1) \qquad \hat{\beta}_{DiD} = \frac{1}{n_1}\sum_{i\in I_1}\left[\left(Y_{1i}^{after} - Y_{0i}^{before}\right) - \sum_{j\in I_0} w(i,j)\left(Y_{0j}^{after} - Y_{0j}^{before}\right)\right]$$

The literature has often employed propensity score matching to find weights $w(i,j)$ to construct a comparison group that has on average observable characteristics similar to those of the treatment group prior to the treatment (Caliendo & Kopeinig, 2008; see, e.g., Dehejia & Wahba, 2002).[11] In this paper, we rely on entropy balancing instead of propensity scores to construct the weights $w(i,j)$ (Hainmueller, 2012). Entropy balancing is a nonparametric reweighting technique that is more effective in reducing covariate imbalance than propensity score matching (see, e.g., Marcus, 2013; Ruhose et al., 2019, for applications). At the heart of the method lies an optimization algorithm that reweights the observations in the comparison group such that the covariates of the comparison group satisfy prespecified balancing constraints. In our application, we require the same mean and variance of the conditioning variables as in the treatment group (see Table 1). Most importantly, we condition on the yearly income and the unemployment experience in 2014 and 2015. This flexible matching on the pretreatment labor-market trajectory also addresses comparison issues arising from a potential Ashenfelter dip (Ashenfelter, 1978) prior to the training participation. Since we have no information about the hours worked, we condition on being in full-time employment in 2016 (information from the MET data) to proxy for the intensive labor supply margin. Moreover, we condition on demo-

[11] The propensity scores are estimated probabilities to receive the treatment. They are used to find nontreated units with similar treatment propensities (e.g., as in nearest neighbor matching), and they also can be used directly to weight the units in the comparison group (inverse probability weighting).

graphic characteristics such as gender, age, marital status, children, citizenship status, and region of residence. We also condition on education in five categories and occupational groups in six categories. All these variables are based on 2016 observations and come from the MET data.

Entropy balancing has four major advantages over propensity score matching. First, entropy balancing makes it unnecessary to check balancing after applying the weights to the observations in the comparison group since covariate differences between the treatment and comparison groups are equalized *by construction*. Second, we not only equalize differences in averages between the treatment and comparison groups before treatment but also equalize differences in the variance of outcomes. For example, the standard deviation on log yearly earnings in 2015 is equal to 0.99 in the comparison group (approximately 9.3 percent of the comparison group mean), whereas it is equal to only 0.74 in the treatment group (approximately 7.0 percent of the comparison group mean). Third, we show above that our pool of potential comparison units is almost as large as the pool of treated units, which is a specific feature of the Swiss adult education sector. Propensity score matching, however, usually requires a larger pool of potential comparison units to find satisfying matches. Entropy balancing ensures a much quicker convergence in the weights that yield a satisfactory control group. Fourth, the method relies much less on (subjective) specification choices, which usually have a strong effect on the results when using propensity score matching.

The estimator from Equation (1) is implemented in two steps. In the first step, we construct the weights $w(i,j)$ using entropy balancing. In the second step, we estimate a difference-in-differences regression with the weights obtained in the first step. The estimator is similar to the traditional difference-in-differences estimator in that it partials out selection on unobservables that are time-invariant. In addition, however, we also partial out all differences in observable characteristics that we have included in the first step of the procedure. To give the estimates a causal interpretation, we must assume that no unobserved variables exist that simultaneously influence changes in labor market outcomes and the probability of training participation. That is, the labor market outcomes of treated individuals would have followed the same trend that we observe for the matched comparison group in the absence of treatment. Formally, this means:

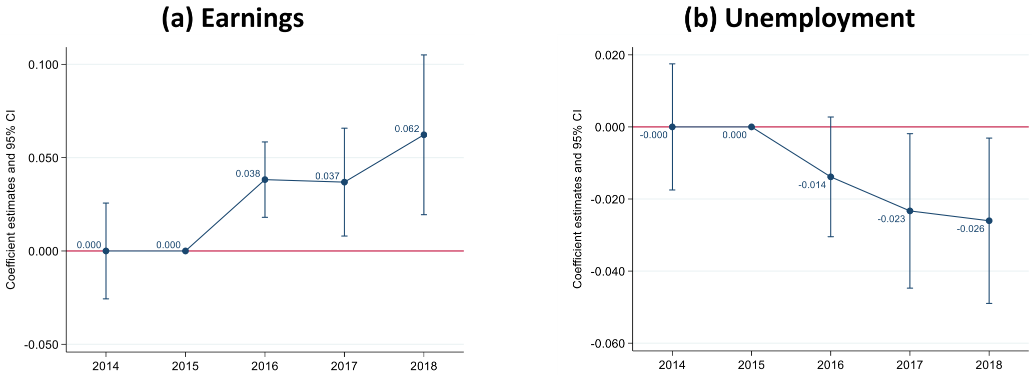
$$(2) \qquad E\left[Y_0^{after} - Y_0^{before} | EB(X), D = 1\right] = E\left[Y_0^{after} - Y_0^{before} | EB(X), D = 0\right]$$

where $EB(X)$ refers to the weights obtained from entropy balancing.

5. Results

In Figure 2(a) and Column 1 of Table 2, we show significant earnings returns on participation in work-related CET. While the effect in 2014 is zero by construction, we find that the participants of work-related training earn 3.8 percent more than individuals who did not participate in adult education in the year of the treatment (2016). This effect remains stable in 2017 and increases up to 6.2 percent in 2018. Averaged over the posttreatment period (years 2017 and 2018), the effect of work-related training amounts to 4.8 percent (Column (3) in Table 2), which is in line with the effects found in other countries (Muehler et al., 2007; Novella et al., 2018; Ruhose et al., 2019).[12]

Figure 2: Training effects on earnings and unemployment



Notes: The figure shows the results of training participation on log yearly earnings (a) and unemployment status (b). Columns (1) and (2) in Table 2 provide the corresponding regression results. The reference period is equal to 2015 (t=-1). Observations in the comparison group are weighted by balancing weights. Ninety-five percent confidence intervals are plotted and obtained from standard errors that are clustered at the individual level.
Data sources: Swiss Microcensus on Education and Training (MET), Central Compensation Office (CCO), and State Secretariat for Economic Affairs (SECO).

For unemployment, the coefficients of the difference-in-differences model also reveal statistically significant effects of work-related CET within the years after the treatment (see Figure 2(b) and Column 2 of Table 2). Again, while there are no pretreatment differences between the treatment and control groups by construction, training participation reduces the risk of unemployment by 1.4 percentage points in the treatment period (the coefficient is insignificant at conventional levels), which decreases further to 2.3 percentage points and 2.6 percentage points in 2017 and 2018, respectively.[13] On average, we observe a decrease in the unemployment probability by 2.5 percentage points after training participation (Column (4) of Table (2)). Compared to the unemployment rate in the comparison group in 2015 (8.8 percent), this implies that training participation lowers the average unemployment risk by about a third on average.

[12] The results are very similar when we estimate the model on a balanced panel (see Appendix Table A.3).
[13] In further analyses, we also estimated the effect of training on the duration of unemployment and the probability of reintegration, but we did not find any significant results. However, we do not take this as decisive evidence against an effect of training on these outcomes because of the small sample size (i.e., low percentage of unemployed individuals within the data) and the short time window after training participation (only three years). The results are available from the authors upon request.

Table 2: Main results

	Yearly effects		Average effects	
	Log yearly earnings	Unemployed	Log yearly earnings	Unemployed
	(1)	(2)	(3)	(4)
Training x 2018	0.062***	-0.026**		
	(0.022)	(0.012)		
Training x 2017	0.037**	-0.023**		
	(0.015)	(0.011)		
Training x 2016	0.038***	-0.014		
	(0.010)	(0.008)		
Training x 2014	0.000	-0.000		
	(0.013)	(0.009)		
Training x post			0.048***	-0.025***
			(0.017)	(0.009)
R-squared	0.010	0.003	0.006	0.004
Observations	29,012	29,062	23,183	23,231

Notes: The table shows the results of training participation on log yearly earnings and unemployment status. The reference period in Columns (1) and (2) is 2015. Observations in the comparison group are weighted by balancing weights. The treatment year 2016 in Columns (3) and (4) is omitted. Standard errors are clustered at the individual level and reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Data sources: Swiss Microcensus on Education and Training (MET), Central Compensation Office (CCO), State Secretariat for Economic Affairs (SECO).

6. Effect heterogeneity

In addition to the overall average effects, this section analyzes the potential effect heterogeneity according to individual characteristics (6.1) and the regional labor market context (6.2).

6.1 Individual characteristics

The analyses reveal that the average results conceal a fair amount of heterogeneity. Table 3 shows that the earnings effect as well as the effect on unemployment reduction is primarily driven by male workers. They benefit from a much higher average training effect on earnings (6.7 percent versus 4 percent) and a reduction in unemployment risk (-3.3 percentage points versus -2.3 percentage points) than females. The earnings effects are more pronounced for prime age workers, i.e., workers at the age of 30 to 50 years, while there are no discernible differences in the unemployment reduction for different age groups, although the effect is largest (but not statistically different from zero) for individuals between 50 and 60 years of age.[14] Overall, the results suggest a systematic pattern throughout the life cycle: earnings effects are strongest for prime-age workers who are in the midst of their carriers and likely at the peak of the age–earnings profile. With advancing age, the benefit of CET is not so much a higher wage but rather insurance against an increased risk of unemployment.[15]

[14] While we decided to choose age groups that cover the entire age range, we also tried different age categories. These analyses show that the old-age unemployment effect concentrates in the age group between 45 and 55 years. There, unemployment is reduced by 3.7 percentage points, which is significant at the 5 percent level. These results are available from the authors upon request.

[15] We find no heterogeneity regarding the duration of training activities. Analyses of different quantiles (terciles and quartiles) produce mostly statistically nonsignificant results.

Table 3: Heterogeneity by individual characteristics

	Log yearly earnings			Unemployed		
	(1)	(2)	(3)	(4)	(5)	(6)
Gender	**Male**	**Female**		**Male**	**Female**	
Training x post	0.067***	0.040		-0.033**	-0.023	
	(0.024)	(0.026)		(0.014)	(0.015)	
R-squared	0.005	0.007		0.004	0.005	
Observations	11,792	11,391		11,813	11,418	
Age groups	**20-29**	**30-49**	**50-60**	**20-29**	**30-49**	**50-60**
Training x post	-0.019	0.052**	0.030	-0.015	-0.022	-0.030
	(0.058)	(0.024)	(0.024)	(0.019)	(0.014)	(0.024)
R-squared	0.147	0.002	0.016	0.002	0.002	0.011
Observations	3,968	12,170	7045	2,052	6,596	4,112
Education	**Unskilled**	**Vocational**	**General**	**Unskilled**	**Vocational**	**General**
Training x post	0.045	0.041**	0.034	-0.001	-0.030***	-0.019
	(0.062)	(0.021)	(0.036)	(0.035)	(0.012)	(0.017)
R-squared	0.010	0.002	0.018	0.001	0.003	0.002
Observations	2,138	13,056	7,971	2,147	13,080	7,986
Finance model	**Self-financed**	**Firm-financed**		**Self-financed**	**Firm-financed**	
Training x post	0.031	0.048***		-0.018	-0.026***	
	(0.028)	(0.017)		(0.015)	(0.009)	
R-squared	0.004	0.006		0.001	0.005	
Observations	10,383	19,905		10,421	19,944	

Notes: The table shows the results of training participation on log yearly earnings (Columns (1) to (3)) and unemployment status (Columns (4) to (6)) for the subgroups specified in the column headers. Observations in the comparison group are weighted by balancing weights that are computed for each subgroup separately. The treatment year 2016 is omitted. Standard errors are clustered at the individual level and reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Data sources: Swiss Microcensus on Education and Training (MET), Central Compensation Office (CCO), and State Secretariat for Economic Affairs (SECO).

Regarding formal education level, our heterogeneity analyses show statistically significant earnings- and unemployment-reducing effects only for those with vocational or professional education and training.[16] The earnings effects for people with no postcompulsory education are similar in size to those for people with vocational education, although not statistically different from zero, while the effect on unemployment is zero. For individuals who followed general education, either on the upper-secondary level (university entrance diploma: baccalaureate) or university education, all effects are smaller in size and statistically not different from zero. This suggests that CET can be an important measure to prevent or compensate for the devaluation of occupation-specific skills in the course of working life, especially for people with vocational training (Hanushek et al., 2017).

Finally, the differentiation between self-financed or employer-financed CET shows that the positive effects of CET are more pronounced for the latter, as in other studies(Ehlert, 2017; Vignoles et al., 2004).

[16] Our category "vocational" includes vocational education training at the upper-secondary and tertiary levels (Professional Education and Training; PET). Specifications with separate categories for upper-secondary and tertiary-level degrees show no statistically significant effects; only the comprehensive category of all forms of vocational and professional education shows such effects. We conclude from this that the statistically significant effect of the category "tertiary" education (not reported here) is basically due to the group of people with professional education.

6.2 Labor market context

Regional labor markets differ considerably in their local labor market conditions. For example, employment rates across the Swiss cantons vary from 79.8 percent in the canton of Ticino to 90.3 percent in the canton of Uri (in the years 2014/2015).[17] In the same years, unemployment rates varied from 1.4 percent in the canton of Uri to 10.6 percent in the canton of Geneva.[18] Moreover, urbanization rates in Switzerland—measured by the density of the population (city, agglomeration, rural village) from 2016—differ considerably. Given these large differences among local labor markets, it is natural to ask whether the labor market effects of CET are the same or different in all labor markets. Table 4 shows the results of our heterogeneity analysis according to the labor market context. The balancing weights are computed for each subgroup separately to obtain a valid comparison group within each stratum.

The results in Table 4 reveal four noteworthy patterns. First, we find strong (above-average) training effects on earnings and unemployment in economically weak regions (those with a low employment rate combined with a high unemployment rate), as shown in Columns (1) and (6) of Table 4. Second, we find strong (above-average) training effects on unemployment in economically strong regions (those with a high employment rate and a low unemployment rate), as shown in Panel B, Columns (3) and (4). Third, the training effects are relatively modest in regions with about average employment but also high unemployment rates. Fourth, distinguishing between urban and rural areas in Columns (7) and (8) shows that the positive effects are visible only in urban regions.

Our data do not allow us to study the detailed mechanisms behind these different effects. Thus, we can only speculate about the potential channels. The strong training effect in economically weak regions is more intuitive and may indicate that training helps to distinguish trained workers from inactive workers in terms of continuing education, which leads to higher earnings and employment. At the same time, firm investments in CET, when regional economic conditions become rough, are an alternative to lowering wages or increasing layoffs to fight the negative economic environment. The finding that CET also reduces the risk of unemployment in the strong labor market, on the other hand, may be a result of higher hiring and search costs of firms in labor markets with fewer available (unemployed) candidates. With the help of CET, companies can try to better retain employees (loyalty and training contracts) and thus keep turnover rates in the workforce low.

[17] The employment rate is constructed by dividing the employed 20- to 60-year-olds by the total of the population (20 to 60 years) and refers to the means in 2014 and 2015. The data are provided by the Swiss Federal Statistical Office.

[18] The data for the cantonal unemployment rate refer to the average in 2014 and 2015 and are provided by the Swiss Federal Statistical Office.

Table 4: Heterogeneity by regional labor market characteristics

	Regional employment rate			Regional unemployment rate			Urbanization	
	q1	q2/q3	q4	q1	q2/q3	q4	Urban	Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: log yearly earnings								
Training x post	0.074**	0.042*	0.030	0.046	0.026	0.071*	0.055***	0.015
	(0.034)	(0.024)	(0.041)	(0.039)	(0.024)	(0.036)	(0.021)	(0.034)
R-squared	0.004	0.007	0.009	0.006	0.008	0.004	0.008	0.002
Observations	6,264	11,568	5,351	7,585	10,298	5,300	17,075	6,076
Panel B: unemployed								
Training x post	-0.043**	-0.005	-0.076**	-0.040**	-0.010	-0.034	-0.031***	-0.006
	(0.022)	(0.012)	(0.034)	(0.019)	(0.012)	(0.023)	(0.012)	(0.018)
R-squared	0.014	0.000	0.025	0.008	0.000	0.011	0.004	0.001
Observations	6,276	11,598	5,357	7,597	10,324	5,310	17,115	6,084

Notes: The table shows the results of training participation on log yearly earnings (Panel A) and unemployment status (Panel B) for the subgroups specified in the column headers. Observations in the comparison group are weighted by balancing weights that are computed for each subgroup separately. The treatment year 2016 is omitted. Standard errors are clustered at the individual level and reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Data sources: Swiss Microcensus on Education and Training (MET), Central Compensation Office (CCO), State Secretariat for Economic Affairs (SECO).

7. Conclusion

A few decades ago, nonformal continuing education and training (CET) was propagated primarily as a means for adults to close gaps in their formal education in their later working life. However, in the face of accelerating structural change and digitalization, CET has become a necessity for a broad segment of the workforce, especially formally highly qualified individuals. The latter are particularly vulnerable to a depreciation of their human capital over time and therefore need to continuously invest in it. Structural change forces them not only to change their occupational field or sector but also to maintain their skill level in their traditional occupation.

Against this background, it is astonishing how narrow the empirical literature is that has investigated the economic benefits of CET, especially in comparison to the countless studies on the returns of formal education. Two reasons may be decisive for this. First, there is great heterogeneity and constantly changing offers in adult education relative to formal qualifications. Second, the fact that selection into further education, and thus the potential biases in the estimates of the effects, are even more relevant in further education than in formal education pathways.

In this paper, we attempt to make a new contribution to the literature by estimating labor market returns (wages and reduction of the risk of becoming unemployed) using a novel dataset that combines census data on individual training activity with register data on income and unemployment. This dataset allows us, on the one hand, not to rely on self-reported data on labor market returns and, on the other hand, to consider a longer period of time before and after the training, which allows us to construct a comparable control group to our treatment group. We do this by applying a regression-adjusted matched difference-in-differences approach with entropy balancing to account for selection bias and sorting on gains.

The empirical data come from Switzerland, which is interesting for at least three reasons. First, Switzerland is one of the countries with the highest average CET participation, at least in a European comparison. Second, in contrast to other countries with high participation rates, this CET is mostly privately organized, with only a few state interventions. Third, the labor market is also fairly liberalized and, as far as the strength of labor market regulation is concerned, corresponds more to Anglo-Saxon countries than to continental European countries.

The empirical results document that on average, training participation increases earnings by 4.8 percent and reduces the risk of becoming unemployed by 2.5 percentage points, which is a large relative effect, given that unemployment rates are quite low in Switzerland.

Furthermore, we document an interesting, substantial effect heterogeneity. The analysis shows that the returns on work-related training are particularly high for male workers at the peak of their professional career, that is, the prime age of approximately 45 years. We further find that workers with vocational education and training benefit more from work-related training in terms of earnings and employment than workers with general education. This suggests that training returns are particularly strong for those who had acquired mainly occupation-specific skills and are more at risk of skill obsolescence when the structural and technological changes are fast.

Finally, we document that training effects are context specific: training returns are higher in depressed labor markets, that is, those regions that are characterized by low employment rates and high unemployment rates. In addition, CET also yields higher returns in relation to the reduction of the risk of becoming unemployed in booming labor markets with a high employment rate and low unemployment rate.

While our paper shows effect sizes of CET that are comparable to those of other countries in terms of earnings, we also provide evidence on the benefit of CET for reducing the risk of becoming unemployed. In this sense, CET can yield a double dividend for those benefiting from it. The pronounced effect heterogeneity, however, also shows that CET is not working for everyone in every context, which is something to consider when investing time and money in CET.

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Appendix

Table A.1: Descriptive statistics for each federal state (canton)

Canton	Full sample	Training participants	Comparison group	
	Average	Average	Difference to (3)	p-value of (5)
(1)	(2)	(3)	(4)	(5)
Aargau	0.074	0.072	0.005	0.165
Appenzell	0.006	0.006	-0.002	0.076
Bern	0.097	0.103	-0.024	0.000
Basel-Landschaft	0.037	0.039	-0.003	0.224
Basel-Stadt	0.033	0.034	-0.006	0.005
Freiburg	0.033	0.032	0.004	0.058
Genève	0.039	0.035	0.010	0.000
Glarus	0.002	0.002	0.000	0.858
Graubünden	0.019	0.019	0.002	0.181
Jura	0.007	0.007	0.002	0.090
Luzern	0.115	0.116	-0.004	0.291
Neuchâtel	0.016	0.014	0.008	0.000
Unterwalden	0.008	0.008	-0.001	0.567
St. Gallen	0.047	0.046	0.005	0.051
Schaffhausen	0.006	0.007	-0.003	0.002
Solothurn	0.034	0.032	0.007	0.003
Schwyz	0.017	0.016	0.004	0.011
Thurgau	0.027	0.029	-0.011	0.000
Ticino	0.067	0.057	0.039	0.000
Uri	0.005	0.005	-0.002	0.027
Vaud	0.066	0.065	0.006	0.076
Valais	0.042	0.041	0.004	0.165
Zug	0.013	0.012	0.001	0.574
Zuerich	0.188	0.203	-0.041	0.000

Notes: The table shows descriptive statistics for the distribution of observations across cantons in the year 2015. We use a simple t test to test for the significance of the difference between the training participants and the comparison group.

Data sources: Swiss Microcensus on Education and Training (MET), Central Compensation Office (CCO), and State Secretariat for Economic Affairs (SECO).

Table A.2: Sample construction

Sample	Sample restriction	Person/year observations	Unique persons
Total sample	Total of matched sample (5 year waves)	54,019	11,509
	Only working age population (20-60 years)	38,763	8,059
	Only employed in 2016 (no self-employment)	32,598	6,712
	Drop if earnings information for all years are missing	32,410	6,679
	Drop if earnings information are only available for the post-treatment period	32,296	6,608
	Drop if earnings information is not available for the pre-treatment years (2014 and/or 2015)	31,486	6,356
	Treatment categorization		
	Work-related training (treatment)	20,777	4,179
	No training (comparison)	8,285	1,681
	Other type of training only (dropped)	2,424	496
Analytical sample (treatment and comparison)		29,062	5,860
Strongly balanced analytical sample		28,325	5,665

Notes: The table shows the construction of the analytical sample. The sample size is shown for the unemployment sample.
Data sources: Swiss Microcensus on Education and Training (MET), Central Compensation Office (CCO), and State Secretariat for Economic Affairs (SECO).

Table A.3: Main Results in Strongly Balanced Panel

	Yearly effects		Average effects	
	Log yearly earn-ings	Unemployed	Log yearly earnings	Unemployed
	(1)	(2)	(3)	(4)
Training x 2018	0.064***	-0.028**		
	(0.022)	(0.012)		
Training x 2017	0.035**	-0.026**		
	(0.014)	(0.011)		
Training x 2016	0.034***	-0.016*		
	(0.010)	(0.009)		
Training x 2014	0.000	-0.000		
	(0.013)	(0.009)		
Training x post			0.049***	-0.027***
			(0.017)	(0.009)
R-squared	0.014	0.003	0.009	0.004
Observations	28,325	28,325	22,660	22,660

Notes: The table shows the results of training participation on log yearly earnings and unemployment status. Reference period in Columns (1) and (2) is equal to 2015. Observations in the comparison group are weighted by balancing weights. The treatment year 2016 in Columns (3) and (4) is omitted. Standard errors clustered at the individual level reported in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Data sources: Swiss Microcensus on Education and Training (MET), Central Compensation Office (CCO), and State Secretariat for Economic Affairs (SECO).