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Labor market returns to college education with vocational qualifications*

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ABSTRACT

In this paper, I assess labor market returns of a substantial skill upgrade: college enrollment of the vocationally trained, non-traditional students who do not have the formal entry requirement. Using propensity-score-adjusted regressions and the National Educational Panel Study, I find that these enrollees face high opportunity costs as they forgo earnings during the enrollment period. In the long-run, enrollees tend to obtain higher cumulative earnings than those who continue with a vocational-training-based career, but, there is a large degree of uncertainty. On the positive side, enrollees attain jobs with a higher reputation in society, hinting at sizable non-monetary returns.

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1. Introduction

Demographic and technological changes currently challenge labor markets in developed countries. Today's workforce may fail to meet future skill requirements. Therefore, lifelong learning and profound skill upgrades at later stages in life are becoming increasingly important. In many developed countries, there is a policy trend to viewing higher education as part of lifelong learning and making higher education more accessible to non-traditional students. This trend has led to a diversified student body, now including students who are older or who do not have the traditional entry qualifications (Slowey and Schuetze 2012; Wolter and Kerst 2015). However, little is known about the labor market returns of higher education for these non-traditional students, the focus of this paper.

Opening higher education to non-traditional students is also of interest from an equality-of-opportunities perspective. Many countries assign their students into vocational and academic tracks even before they are 14 years old (for instance, Austria, Belgium, Czech Republic, Germany, the Netherlands, Slovak Republic, Switzerland (OECD 2012)). At this age, the risk of wrong track-assignment and thereby an increase of education inequality are particularly high (Hanushek and Woessmann 2006). Therefore, it is important that track changes are feasible at later ages. For instance, in Germany, when students do upgrade from the vocational to the academic track after 10th grade, they appear to be as successful in terms of education and labor market outcomes as students

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*This study uses the weakly anonymous National Educational Panel Study (NEPS): Starting Cohort 6 - Adults (Adult Education and Lifelong Learning), doi:10.5157/NEPS:SC6:5.1.0, linked to administrative data of the IAB (Years 1975–2012) by the German Record Linkage Center (GRLC). Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and remote data access. The NEPS data was collected as part of the Framework Program for the Promotion of Empirical Educational Research funded by the German Federal Ministry of Education and Research (BMBF) from 2008 to 2013. As of 2014, NEPS is carried out by the Leibniz Institute for Educational Trajectories (LIfBi) at the University of Bamberg in cooperation with a nationwide network.

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who pursued the academic education track from the start (Dustmann, Puhani, and Schönberg 2017). However, an open question remains as to what benefits can be expected from upgrading at a later point in an educational career, i.e. after finishing vocational training.

In 2009, Germany's education ministers agreed to ease and harmonize college access in all federal states for individuals with vocational training but no formal entry qualification (KMK 2009). This policy facilitates lifelong learning and a skill upgrade from vocational to academic education. Despite eased access to college, these non-traditional students do not constitute a large part of the student body. In 2003, they made up 0.9% of all first semester students, and in 2013, only 2.7%.¹ So far, it is not known why so few enroll in college based on vocational qualifications.²

In this paper, I investigate whether low labor market returns may explain this relatively low take-up. In particular, I analyze how well individuals who enroll in college fare on the labor market in terms of employment probability, job prestige, monthly and cumulative earnings. I compare the findings to those who continue with a vocational-training-based career. I estimate propensity-score-adjusted regressions using the adult cohort of the National Educational Panel Study (NEPS).

I contribute to the existing literature on lifelong learning of the workforce, which has studied (1) returns to on-the-job training and (2) returns to studying for mature students. The first strand of literature focuses on the returns to short-term, work-related training interventions and often finds insignificant wage returns (see for instance, Leuven and Oosterbeek 2008; Görlitz 2011). The second strand investigates the returns to studying for mature students, i.e. individuals who are older than the main student body. For example, a series of studies in Nordic countries compares the labor market outcomes of mature students who take classes at the secondary or university level to the outcomes of individuals who do not study. All find positive returns to earnings but to varying degrees (Hällsten 2012; Stenberg, de Luna, and Westerlund 2014; Böckerman, Jepsen, and Haapen 2015).

In contrast to this previous literature, I focus on college-level studies for the vocationally trained who lack the formal college entry requirement: an *Abitur*. This group has received less attention but is interesting for two reasons. First, it constitutes about 25 million workers, two thirds, of the German labor force (Federal Statistical Office 2015a), and may be particularly affected by technological change. At the same time, evidence suggests that the vocationally trained adapt less flexibly to such changes than those with academic education (Hanushek et al. 2017). But we know little about the labor market benefits of formal tertiary education for this group. Given that enrolling in college would equip them with more general skills, which may complement their vocational skills (Tuor and Backes-Gellner 2010), positive effects on employment and earnings could be expected. However, the vocationally trained face high opportunity costs since they give up the secure employment and income that characterize the early phase of vocational-training-based careers. These opportunity costs may exceed any positive monetary returns to enrollment.

My findings suggest that college enrollment based on vocational qualifications entails high opportunity costs, which may be off-set by higher long-run cumulative earnings and sizable non-monetary returns. Compared to those who continue with a vocational-training-based career, enrollees are 39% less likely to be employed shortly after finishing vocational training and forgo earnings while enrolled. Only on average 20 years after finishing vocational training do enrollees attain the same cumulative earnings as the control group, who did not enroll. Yet, confidence intervals are wide. Hence, recouping the opportunity costs is a lengthy and uncertain process. Furthermore, the average return rates for one year of college education amount to 4.9% for vocationally qualified enrollees. This implies, that non-traditional students realize lower return rates than traditional college students. However, there are possibly sizable non-monetary returns: enrollees score up to 35 points higher on the Magnitude Prestige Scale, a job prestige measure, spanning from 20 to 186.8, than those who do not enroll. Enrollees thus advance into different occupations than were available to them prior to college enrollment. Enrollees may derive utility from the higher reputation society associates with these occupations.

The remainder of this paper is structured as follows: Section 2 describes the empirical strategy. Section 3 presents the matching quality, the main results, and a heterogeneity and sensitivity analysis. Section 4 concludes.

2. Empirical strategy

2.1. Method

Assessing a treatment in the potential outcomes framework (Rubin 1974), one ideally compares the potential outcome of the treated when treated (y^T) and when not treated (y^C). However, I only observe individuals either in the treatment group, those who enrolled in college based on vocational qualifications, or in the control group, those who continue with a career based on vocational qualifications. As with all education decisions, the decision to enroll in college is selective for non-traditional students (Card 1999). Therefore, the simple difference between treatment and control group produces biased results.

In the literature, many authors use an instrument such as distance to nearest college for educational attainment to introduce exogenous variation (e.g. Card 1995). However, distance between the region of vocational training to the nearest university or college of applied sciences is not statistically or economically significantly related to enrollment in college based on vocational training.³ In addition to this non-correlation, the exclusion restriction may not hold: the sorting of vocationally trained individuals into regions could be driven by factors that are also correlated with labor market outcomes. Hence, this instrumental variable is not a viable estimation strategy in this application.

Another potential candidate for an instrumental variable is how difficult the entrance for vocationally trained was across the different federal states and over time. The exclusion restriction would hold if one assumes that the potential non-traditional students do not sort into federal states based on labor market prospects. However, due to the small sample of treated individuals there is too little variation on the federal state-decade level to estimate a strong first stage.

Due to these limitations, I turn to a selection on observables design to construct an adequate control group: propensity score matching combined with regression models. This approach classifies as doubly-robust since any imbalances that remain after propensity score matching may be addressed by the covariates used in the regression model (Bang and Robins 2005; Stuart 2010). The estimation equation reads:

$$y_{it} = \alpha + \beta T_i + \mathbf{X}'_i \gamma + \epsilon_i \quad (1)$$

where y stands for the outcome (employment probability, job prestige, log monthly or cumulative earnings) of individual i at time t after finishing vocational training. T is a dummy variable which indicates the treatment status, i.e. whether the individual enrolls in college based on vocational qualification. \mathbf{X} is a vector containing all pre-treatment covariates. ϵ captures the remaining idiosyncratic error.

With this method the identification of a causal effect hinges on the conditional independence assumption (CIA): after controlling for all observable variables that influence selection into treatment the treatment is assumed to be as good as randomly assigned (Caliendo and Kopeinig 2008; Stuart 2010). A further assumption is the sufficient overlap in the propensity scores of treatment and control group.

To select the best-performing matching algorithm in my setting, I run balancing tests on nearest neighbor caliper matching, kernel matching, and radius matching. I select the matching algorithm which minimizes the Mean Bias (after matching) = $100((\bar{x}_1 - \bar{x}_0) / \sqrt{0.5(V_1(x) + V_0(x))})$ (Caliendo and Kopeinig 2008; Stuart 2010) for each covariate x . The indices 1 and 0 indicate the individual treatment status. I then use the weights estimated by the best-performing matching algorithm to adjust the regression. Standard errors are clustered at the federal state and vocational decade level.⁴

Despite a careful selection of the conditioning variables there may still be unobservable characteristics that are not well approximated. Potentially omitted unobservables could be ability and motivation. While the CIA is not testable, I follow Ichino, Mealli, and Nannicini (2008), who propose a simulation-based sensitivity check, to gain an understanding of how strongly omitted unobservable characteristics would influence the estimated ATT. They suggest including a potential unobservable

confounding factor which mimics the influence that an observable covariate has on selection and outcome. The less the ATT estimates including this simulated potential confounder vary the higher the certainty that the CIA holds.

2.2. Data

The analysis uses the NEPS Adult Starting Cohort (Blossfeld, Roßbach, and von Maurice 2011) for all covariates as well as the employment and job prestige outcomes.⁵ The adult cohort covers detailed life course information from birth to adult life for 17,137 individuals born between 1944 and 1986. The panel consists of five waves covering current employment and educational activities, it also provides retrospective information on each individual.

The NEPS data are supplemented with administrative data on earnings from the Integrated Employment Biographies (IEB) which covers the time period 1975–2010 for West Germany. Overall, 74% of NEPS-survey participants agreed to record linkage and were identified in the data (Antoni and Eberle 2015). This linked data set is called NEPS-ADIAB.⁶ Individuals who could not be linked either did not agree to record linkage, were not identifiable in the data with the record linkage variables (name, birth date, gender and address), are self-employed or are employed in the public service and not registered with a social security number. In a robustness check, I estimate the average treatment effects using just the NEPS-ADIAB sample also for labor market outcomes other than earnings and find that the results are very similar.⁷ This suggests that the reasons for non-linkage do not systematically bias my estimations. Therefore, I refer to the NEPS-ADIAB sample only for the earnings estimations in order not to jeopardize statistical power or matching quality for the other outcome variables.

In line with the research question, I restrict the sample to individuals who did not obtain a form of *Abitur*. Individuals who do not indicate a school degree, have inconsistencies in their educational path or who do not have a vocational education spell are omitted from the analysis.⁸ I concentrate on West Germans since prior to the reunification the educational paths to tertiary education were different in East Germany (Lischka 1991). The final sample consists of 5774 individuals.

The observation period covers 30 years after the month the individual finishes his/her vocational training. For individuals with less than 30 years of labor market experience, i.e. those younger than 50 years, the analysis only covers the time period that is already observable in the data. For 81%, 67%, and 53% of the analysis sample I observe at least 20, 25, and 30 years respectively.⁹ Within the observation period, the analysis uses time-windows of six months; this allows for some smoothing in the estimates while still regularly capturing changes in labor market status.

2.2.1. Treatment and control group definition

The treatment in this paper is enrolling into college without the formal requirement, an *Abitur*. This is often referred to as the ‘third educational path’ to college, see Figure 1, (Teichler and Wolter 2004; Dahm et al. 2013). Using the NEPS data, the treatment group is identified by those who indicate enrolling in college based on vocational qualification or those who are observed as enrolling in college without having an *Abitur*. The sample includes 163 treated observations.

In the main specification, individuals who have finished a vocational training and continue with a vocational-training-based career constitute the control group. While they do not enroll in college, control group observations may upgrade their skills on the vocational track.

As a heterogeneity check, I condition on the timing of college enrollment since this timing may influence labor market outcomes and what is measurable during the observation period. To shed some light on the effects of timing, I split the treatment sample at 3.5 years after finishing vocational training, when half of the treated have enrolled in college. ‘Early enrollees’ refers to those who enroll within 3.5 years after finishing vocational training and ‘late enrollees’ are those who enroll later than 3.5 years after their first vocational training. The control group remains the same as in the main specification.

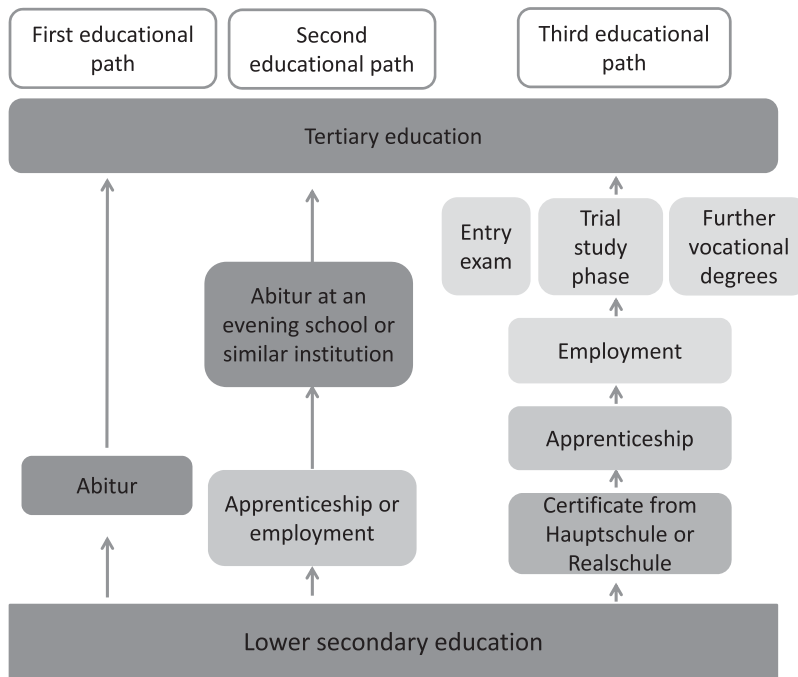


Figure 1. Educational paths to college in Germany. *Source:* Own illustration based on Kamm and Otto (2014).

2.2.2. Conditioning variables

The CIA requires a careful selection of the covariates since they need to capture all the factors that influence enrolling in college education and that could potentially also influence future labor market outcomes (Caliendo and Kopeinig 2008; Stuart 2010). I rely on previous empirical studies as well as theoretical considerations to guide my choice of conditioning variables. The literature identifies anticipated private returns (Hällsten 2012), motivation, ability and aspiration (Lauer and Steiner 2000; Kamm and Otto 2013), and family background (Kirchhoff 1991; Wolter and Reibstein 1991; Black, Devereux, and Salvanes 2009; Hällsten 2012) as decisive factors for both education and labor market outcomes. Therefore, I pay special attention to select variables that approximate these. Table 1 summarizes the final set of conditioning variables and divides them into five categories: demographics, school education, vocational training, regional factors, labor market experience.

I match on pre-treatment characteristics. This means that I rely on variables measured until the individuals finish vocational training. For the heterogeneity check by enrollment timing, I extend the pre-treatment period until 3.5 years after completing vocational training for late enrollees. This makes it possible to include pre-treatment labor market outcomes into the matching process for late enrollees.

2.2.3. Outcome variables

I examine five different labor market outcomes: employment probability, full-time employment probability, job prestige, the log monthly and log cumulative earnings. Employment probability is an indicator variable taking the value 1 when individuals are employed full-time or part-time according to the NEPS data.¹⁰ 5, 15, and 25 years after finishing vocational training the employment probability of the control group reaches 83%, 76%, and 79%, respectively (see Table 2). Full-time employment indicates the probability of working at least 31 hours a week. Conditional on being employed, 93%, 79%,

Table 1. Overview of conditioning variables.

Variable	Definition
<i>Demographics</i>	
Gender	1=male, 0=female
Age at vocational degree	in years
Age at school degree	in years
Migration background	1= if born abroad or father or mother born abroad, 0 otherwise
Education of father and mother	Dummy variables for 4 categories: no school degree, school degree, vocational training, university degree
Difference to highest level of parental education after vocational education	3 categories: lower, same, and higher than that of parents
<i>School education</i>	
Type of school degree	2 categories: lower and intermediate secondary school degree
Final school grade	4 categories: 1–1.9, 2–2.9, 3–3.4, 3.5–5
<i>Vocational training</i>	
Decade of vocational training completion	4 categories: 1950s/60s, 1970s, 1980s, 1990s/2000s
Duration of vocational training	in years
Type of vocational training	Dummy variables for 2 categories: dual apprenticeship and school-based vocational training including health care professions
Occupation of vocational training	Dummy variables of 9 categories based on occupational segments (Matthes, Burkert, and Biersack 2008): metal producer/processor, electronics, construction/interior construction, catering, sales, office/ management, care, medical occupations, others
Firm size of vocational training firm (if it was a dual apprenticeship)	4 categories: below 10 employees, 10–100 employees, 100–2000 employees, 2000 and more employees
<i>Regional factors</i>	
Federal state of vocational training	10 dummy variables for West German federal states
Unemployment rate of federal state upon finishing vocational training	3 categories: regional unemployment rate up to 2.3%, between 2.5–6.5% and more than 6.5% (terciles of the distribution)
<i>Labor market experience (only used for late enrollees)</i>	
Unemployment experience	in months
Number of job changes	number of different job spells
Number of occupational segment changes	number of different occupational segments (Matthes, Burkert, and Biersack 2008)

Notes: Missing observations are captured in a missings dummy in the respective category.

and 72% of the control group work full-time 5, 15, and 25 years after finishing vocational training (see Table 2).

Job prestige is measured by the Magnitude Prestige Scale (MPS) recorded in the NEPS data.¹¹ Using the reputation of an occupation in Germany, the MPS captures the degree of social status associated with a certain occupation. The MPS is constructed by a survey which asks individuals to indicate what reputation they associate with certain occupations listed in the International Standard

Table 2. Descriptive statistics of outcome variables.

Outcome variable	<i>t</i>	Control mean	Number of observations
Employment probability (in percent)	5	82.51	5450
	15	76.89	4816
	25	79.20	3794
Full-time employment probability (conditional on employment, in percent)	5	92.64	4497
	15	79.48	3703
	25	72.08	3005
Magnitude Prestige Scale (points)	5	63.90	4432
	15	67.72	3890
	25	69.32	3215
Log monthly earnings (in logs)	5	7.59	847
	15	7.58	903
	25	7.33	772
Log cumulative earnings (in logs)	5	10.95	1042
	15	12.09	1153
	25	12.63	950

Notes: *t* indicates the years since finishing vocational training.

Classification of Occupations (ISCO) (Wegener 1988). It spans from 20 for construction and maintenance laborers to 186.8 for judges, (Wegener 1988). 5, 15, and 25 years after finishing vocational training the NEPS-sample averages of the MPS amount to 64, 68, and 69 respectively (Table 2). These values are very comparable to the mean MPS for West Germany in 2004 which were 62 for men and 63 for women (Wirth and Frietsch 2001).¹²

The log monthly and cumulative earnings data come from the NEPS-ADIAB. It provides top-coded daily earnings; therefore, I apply the routine suggested by Reichelt (2015) to impute the full daily earnings at the upper end of the distribution.¹³ These daily earnings are summed up to monthly and cumulative earnings, transformed into logs and deflated to 2010 prices, the last year of the NEPS-ADIAB data using the consumer price index. Cumulative earnings are discounted using a rate of 3% which is a common discount factor for long-term investment decisions in Germany. For example, it is used by Börsch-Supan et al. (2004) to model German retirement decisions. Log monthly earnings range between 7.6 and 7.3 log points (Table 2). This corresponds to 1900 and 1500 Euros. Log cumulative earnings increase with years since vocational training from 10.9 to 12.4 log points, which corresponds to approximately 51,000 to 305,000 Euros.

3. Results

3.1. Matching quality

All variables mentioned in Table 1 enter into the propensity score estimation. Interactions or higher order terms of these variables are included in the matching process if it improves balance. I choose the matching algorithm for the main specification which minimizes the mean standardized difference, the mean bias after matching (Caliendo and Kopeinig 2008; Stuart 2010). Given the results of this assessment, I use a 1:35 nearest neighbor matching with caliper .0027 for the main specification.¹⁴

Table A1 in the appendix reports the before and after matching descriptive statistics for all covariates. Prior to matching, the individuals of the control group differ substantially from the treated individuals. However, the propensity score matching eliminates these imbalances. For nearly all covariates the standardized difference is smaller than 5%, which is the critical benchmark value used in the literature to indicate good balancing (Caliendo and Kopeinig 2008). Only for a few variables the standardized bias exceeds this benchmark. This is the case for the dummy variables of the school grades 1–1.9, 3–3.4, and 3.5–5.0, the share of people finishing vocational training in the 1970s, the vocational occupation segment ‘office/management’, the dummy variables for vocational training firms with 10–100 employees and with 2000 and more employees, the dummy indicating mother’s school degree, and the regional unemployment rate category ‘up to 2.3%’. In most cases, the absolute differences between the means are very small. In addition, the doubly-robust estimation approach can deal with these imbalances because the weighted regression also controls for the covariate set used in the propensity score calculation.

Finally, overlap is sufficient as Figure A1 in the appendix displays. Even though the control group’s propensity scores are left-skewed, there are still enough observations to match to the treatment group.

3.2. Main results

The ATT for the probability of being employed displays a clear pattern (Figure 2). Many treated appear to withdraw from the labor market to attend college during the first twelve years after vocational training. 3.5 years after finishing vocational training mark the low point. Then, treated individuals are 39% less likely to be employed than the control group, who pursue a typical vocational-training-based career and have an employment probability of 83%. After this initial phase, those who enroll in college are slightly more likely to be employed than the control group. 17 years after

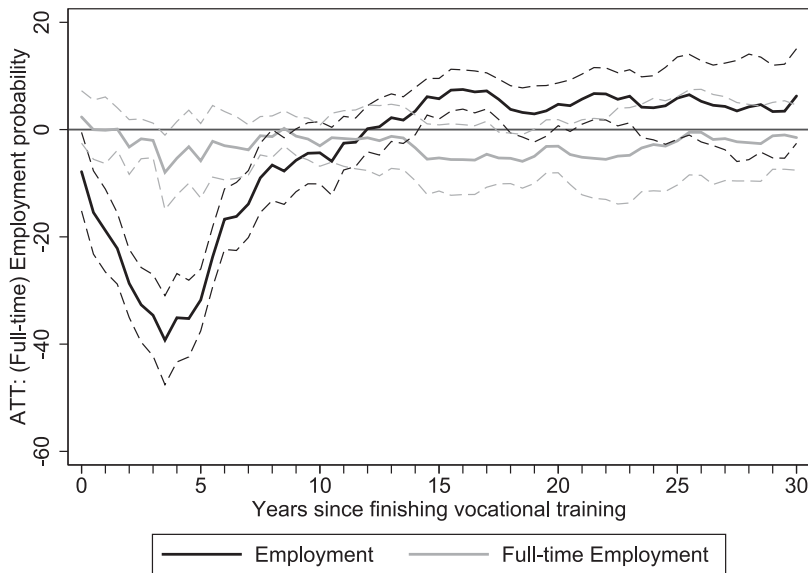


Figure 2. ATT for the probability of being (full-time) employed.

Notes: This figure displays the ATT for the employment probability and full-time employment probability conditional on employment for the main specification. It is measured in percentage point differences. The ATT is calculated using propensity-score-adjusted regression based on nearest neighbor matching using a six-month time window. The point estimates shown are based on at least 25 treated observations. The standard errors are clustered at the federal state and vocational decade level. The dashed lines indicate the 95% confidence interval.

finishing vocational training, for instance, they record a 7.2 percentage points (9%) higher employment probability. However, this effect is not statistical significant for the entire observation period. Figure 2 shows that the treated are not more or less likely to work full-time than the control group. This suggests that the effects of enrolling in college tend to influence the extensive margin more than the intensive margin of labor supply. Overall, the large drop in employment probability during the early career hints at high opportunity costs of enrollees.

In addition, I assess whether enrolling in college has an effect on job prestige as measured by the Magnitude Prestige Scale (MPS), which gives occupations an ordinal ranking. After the initial phase, job prestige increases sharply. Starting ten years after finishing vocational training, the treated have between 26.4 and 35 points higher MPS scores than those of the control group depending on the year measured (Figure 3). To interpret this effect, we take musical instrument makers and tuners (MPS of 63) as a starting point since it is close to the control group's average MPS (63.9) five years after vocational training. 10 points up the prestige ladder are secretaries and fire-fighters (MPS of 73.1), 20 points up are primary education teaching associate professionals and statistical, mathematical and related associate professionals (MPS of 82.9), and 30 points up are accounting and bookkeeping clerks and trade brokers (MPS of 93.6 and 93.9) (Christoph 2005). Hence after enrolling in college individuals obtain jobs with considerable more reputation in society as measured by the MPS than those who continue with their vocational-training-based career. This may increase their utility irrespective of monetary returns of enrolling in college and hints at considerable non-monetary returns to college enrollment based on vocational qualification.

Finally, I investigate the monetary returns to enrolling in college based on vocational training using the NEPS-ADIAB, i.e. those of the NEPS-sample who were linkable to the Sample of Integrated Biographies. The NEPS-ADIAB hence comprises a subsample of the NEPS employees who are covered by the social security system.

Those who remain employed during the enrollment phase earn up to 12.4% less per month than individuals in the control group, who earn on average 1900 Euros per month (Figure 4(a)). Yet, beginning with 9.5 years after finishing vocational training, they steadily earn more per month than the

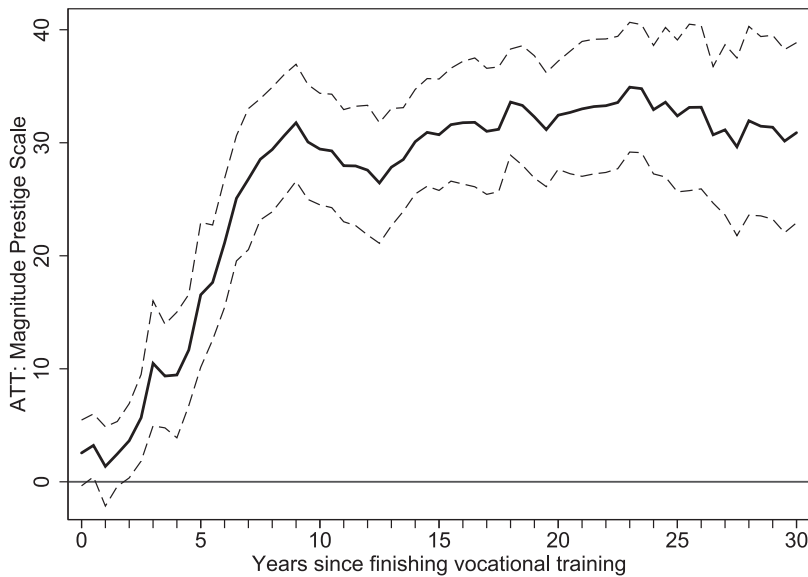


Figure 3. ATT for the job prestige (MPS).

Notes: This figure displays the ATT for job quality measured by MPS for the main specification. The ATT is calculated using propensity-score-adjusted regressions based on nearest neighbor matching using a six-month time window. The point estimates shown are based on at least 25 treated observations. The standard errors are clustered at the federal state and vocational decade level. The dashed lines indicate the 95% confidence interval.

control group. For instance, 15 years after finishing vocational training they earn 16.2% more per month than the control group. This earnings-premium peaks around year 24 after finishing vocational training when the treated earn 34% more per month than the control group.

Yet, the opportunity costs, i.e. the forgone earnings while enrolled, are high and not captured by log monthly earnings. The log cumulative earnings directly depict them (Figure 4(b)) since they account for the cumulative earnings the treatment group could have earned had they not enrolled in college. Five years after vocational training the enrollees have accumulated 63.2% less than the control group. Only in the very long-run, after about approximately 19 years, does the group of enrollees recoup the opportunity costs (Figure 4(b)). After this time, the point estimates tend to be positive. For instance, 26.5 years after finishing vocational training, when the point estimate becomes statistically significant at the 5% level, enrollees have earned 18.5% more than those who remain on the vocational track. But large confidence intervals characterize these estimates. This finding is in line with Tuor and Backes-Gellner (2010) who suggest that combining education on the vocational and academic track seems to be associated with more uncertainty in future earnings.

Neglecting direct costs, the rates of return range between 1.5 and 9.4% per year of college education 19 to 30 years after vocational training. In these years, they are on average 4.9%.¹⁵ These rates of return are in the same range as those previous literature finds for mature students, which range around 1.85 and 2.3% for a year of tertiary education (Hällsten 2012) and 3.8 to 6% for one year of adult secondary education (Stenberg, de Luna, and Westerlund 2014). However, they are lower than the returns to one year of university education found for traditional college students in Germany which lie between 6% (Boockmann and Steiner 2006), 8.7% (Lauer and Steiner 2000), and 10.9% (Ammermueller and Weber 2005). This may be due to the high opportunity costs for vocationally-trained students. Without the college-education, the vocationally-trained would receive higher wages than the traditional students who have the formal college entry requirement but no vocational training.

Another reason why returns are slightly lower than for traditional students may be that individuals choose fields of studies that differ from their vocational field. Indeed, 54% of all treated study in a

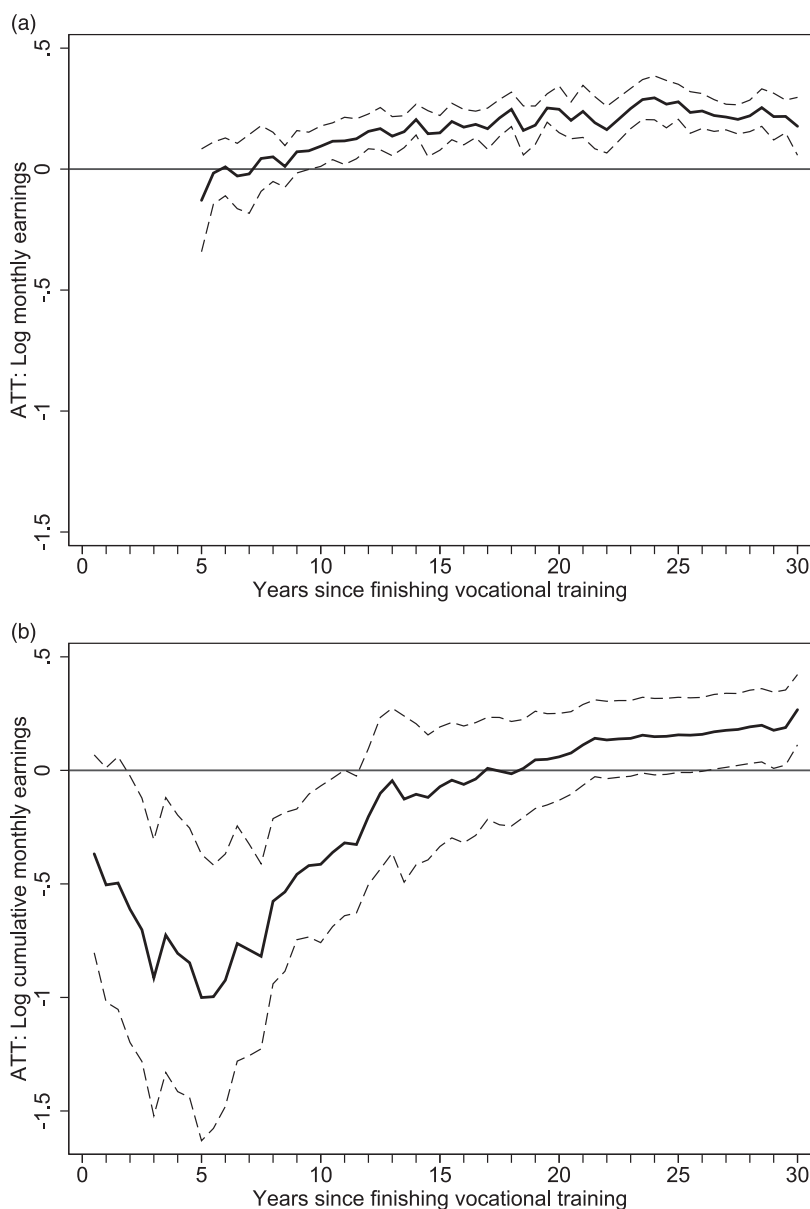


Figure 4. Average treatment effect on earnings. (a) Log monthly earnings, (b) Log cumulative earnings.

Notes: This figure displays the ATT for log monthly earnings and log cumulative earnings for the main specification. The ATT is calculated using propensity-score-adjusted regression based on nearest neighbor matching using a six-month time window. The point estimates are based on at least 25 treated observations. The earnings are deflated to 2010 prices. The cumulative earnings are additionally discounted by a factor of 3%. The standard errors are clustered at the federal state and vocational decade level. The dashed lines indicate the 95% confidence interval.

different occupational segment than their vocational training occupational segment.¹⁶ Table 3 provides a transition matrix between the vocational and college occupational segment for the four most-chosen college fields. Of those who change occupational segments most switch to 'office/management' (27%), followed by 'sciences' (15%), 'care' (8%) and 'metal producer/processor' (8%).

Field choice, however, does not conclusively explain why returns are lower for vocationally-qualified than for traditional students. For one, it may suggest that by enrolling in college the vocationally trained gain access to different kinds of jobs, which would corroborate findings of the education

Table 3. Vocational and college occupational segments.

Origin/Destination Vocational occupational segment	College occupational segment				Total
	Office/management	Sciences	Care	Metal producer/processor	
Green Jobs	1	0	0	0	1
Mining/Chemical industry	0	4	0	0	4
Glas/Ceramics/Paper	2	2	0	0	4
Textile/Leather	0	0	0	1	1
Metal producer/processor	2	3	1	0	6
Electronics	2	0	1	1	4
Wood	1	0	0	0	1
(Interior) Construction	1	1	0	4	6
Catering	0	0	1	0	1
Sales	7	1	2	0	10
Office/management	0	0	1	0	1
Care	1	0	0	0	1
Medical	2	0	0	0	2
Arts/sports	1	0	0	0	1
Total	20	11	6	6	43

Notes: This table shows the origin vocational occupational segment for the four most frequently chosen college occupational segments. The table only includes treated individuals who choose a different occupational segment in their study course than they had in their vocational training.

literature (Dahm et al. 2013). This may mean that their human capital from vocational training becomes somewhat obsolete. For another, even though vocational and academic degrees may not be directly related, i.e. in the same occupational segment, they could still complement each other to some extent (Tuor and Backes-Gellner 2010).

3.3. Heterogeneity by timing of enrollment

The main analysis neglects when the treated enroll. Treatment timing, however, differs greatly by individual. In the main specification, the treatment period spans from the time individuals finish vocational training until 20.5 years later. 50% of the treated individuals are enrolled in college 3.5 years after finishing vocational training and 75% after 7.5 years (Figure 5(a)). All individuals in the sample indicate finishing their studies. The median vocationally-qualified student completes his/her college education 7 years after vocational training. After 11 years, 75% have completed their college education (Figure 5(b)).

This different enrollment timing may affect how labor market returns are measured. Therefore, as a heterogeneity check I divide the treatment group into two groups at the median: the early enrollees, those who enroll within 3.5 years after finishing vocational training and late enrollees, those who enroll later than 3.5 years after their first vocational training.¹⁷ The control group is the same for both early and late enrollees and corresponds to the typical vocational-training-based career.

The labor market returns for the early enrollees mimic those of the main specification, however, they take more extreme values. The employment probability of early enrollees plummets shortly after they finish vocational training. 3.5 years after vocational training they are 55.6% less likely to be employed than the control group (Figure 6). But they re-enter more quickly, reaching the same employment levels as the control group after 7.5 years, and show slightly higher employment levels in the long-run than the control group. Likewise for job prestige, early enrollees enter the more prestigious occupations more quickly (Figure 7).

For late enrollees, point estimates are attenuated compared to the main specification and returns often realize at later points in time. For instance, they withdraw less strongly from the labor market and have a more prolonged period of lower employment levels. Late enrollees reach the same employment levels as the control group only 14 years after finishing vocational training. However, it is difficult to disentangle whether these delayed and attenuated effects are due to the late enrollment per se or due to lower returns for late enrollment.

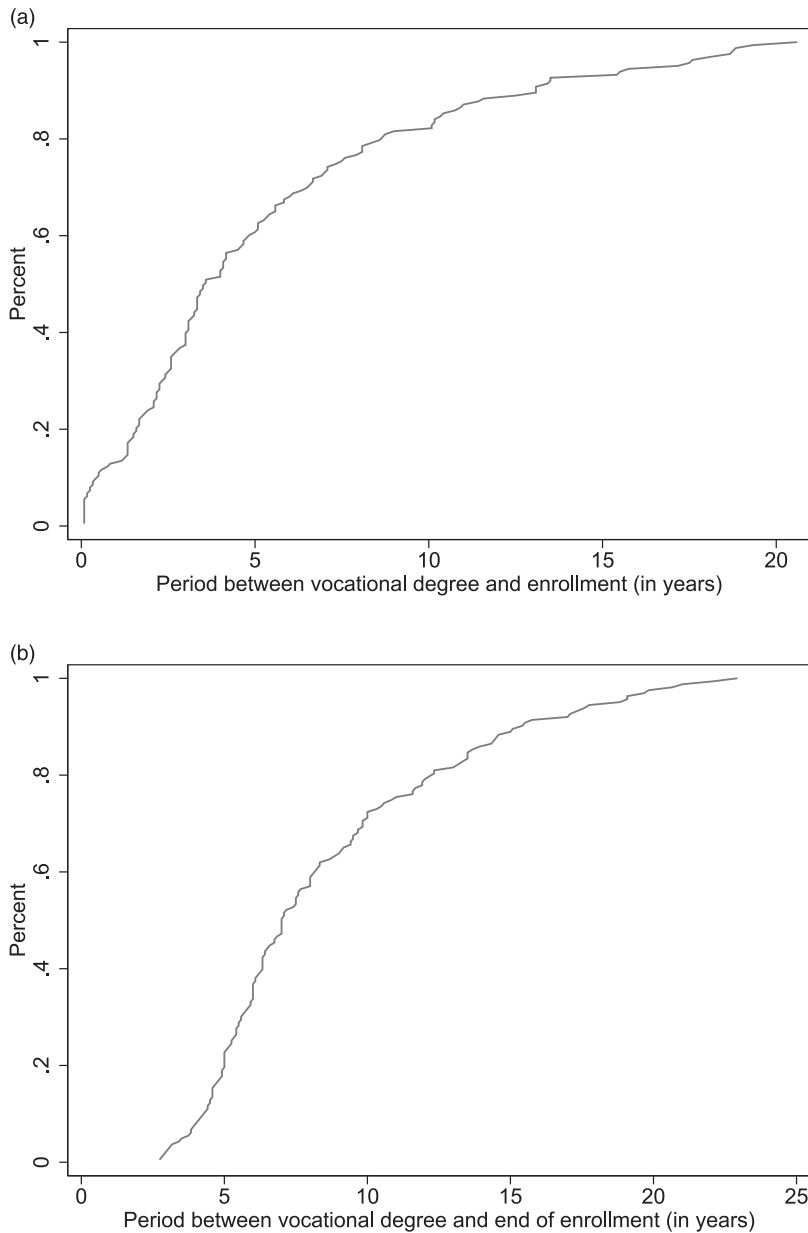


Figure 5. Cumulative distribution of enrollment timing. (a) Beginning of treatment, (b) End of treatment.

Notes: This figure depicts the distribution of enrollment timing (a) and the distribution when the individuals finish their college studies (b).

While both early and late enrollees have higher monthly earnings compared to the control group (Figure 8(a)), only early enrollees recoup the opportunity costs within the observation period (Figure 8 (b)). Initially, early enrollees experience a drop in cumulative earnings by 86.2% compared to those who continue with a vocational-training-based career. This is in line with their large drop in the probability of being employed during the early phase of their career. As their career progresses, they accumulate up to 61.8% more earnings than the control group and recoup the opportunity costs. Their return rates to one year of college range between 1.8 and 19% (14.3% on average) depending on the year.

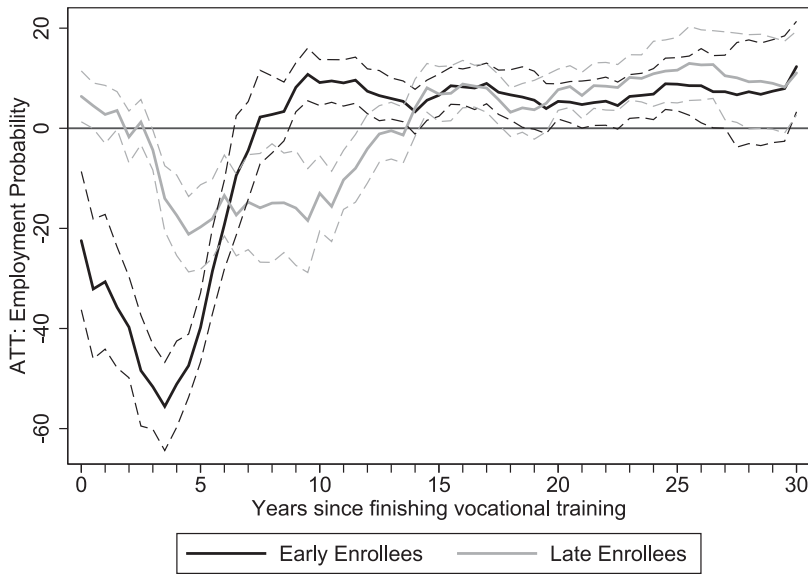


Figure 6. ATT for the employment probability by enrollment timing.

Notes: This figure displays the ATT for the employment probability for early and late enrollees measured in percentage point differences. The ATT is calculated using propensity-score-adjusted regression based on nearest neighbor matching using a six-month time window. The point estimates shown are based on at least 25 treated observations. The standard errors are clustered at the federal state and vocational decade level. The dashed lines indicate the 95% confidence interval.

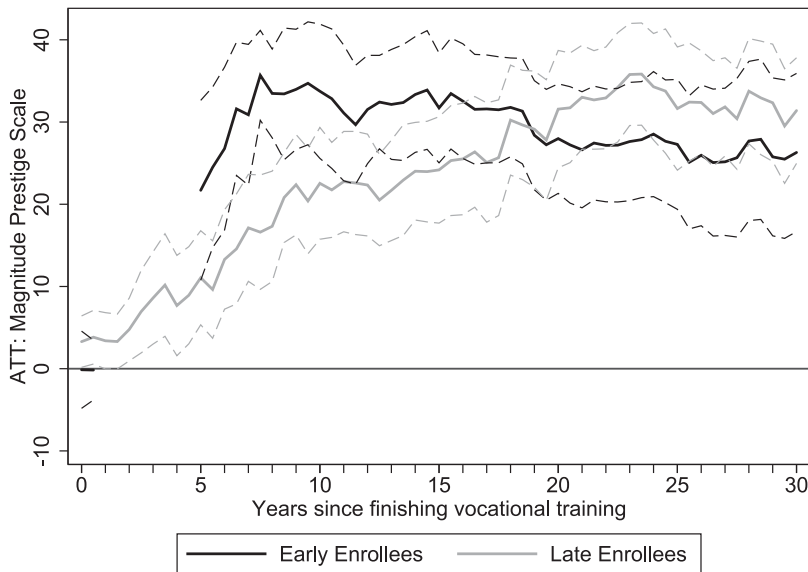


Figure 7. ATT for the job prestige (MPS).

Notes: This figure displays the ATT for job quality measured by MPS by enrollment timing. The ATT is calculated using propensity-score-adjusted regressions based on nearest neighbor matching using a six-month time window. The standard errors are clustered at the federal state and vocational decade level. The dashed lines indicate the 95% confidence interval. Lines are interrupted when there are less than 25 observations in the treatment group.

Late enrollees, on the other hand, do not manage to recoup the opportunity costs within the observation period, despite the positive earnings-premium 10 years after finishing vocational training. Yet, this finding may be the combined effect of lower returns to late enrollment, the limited

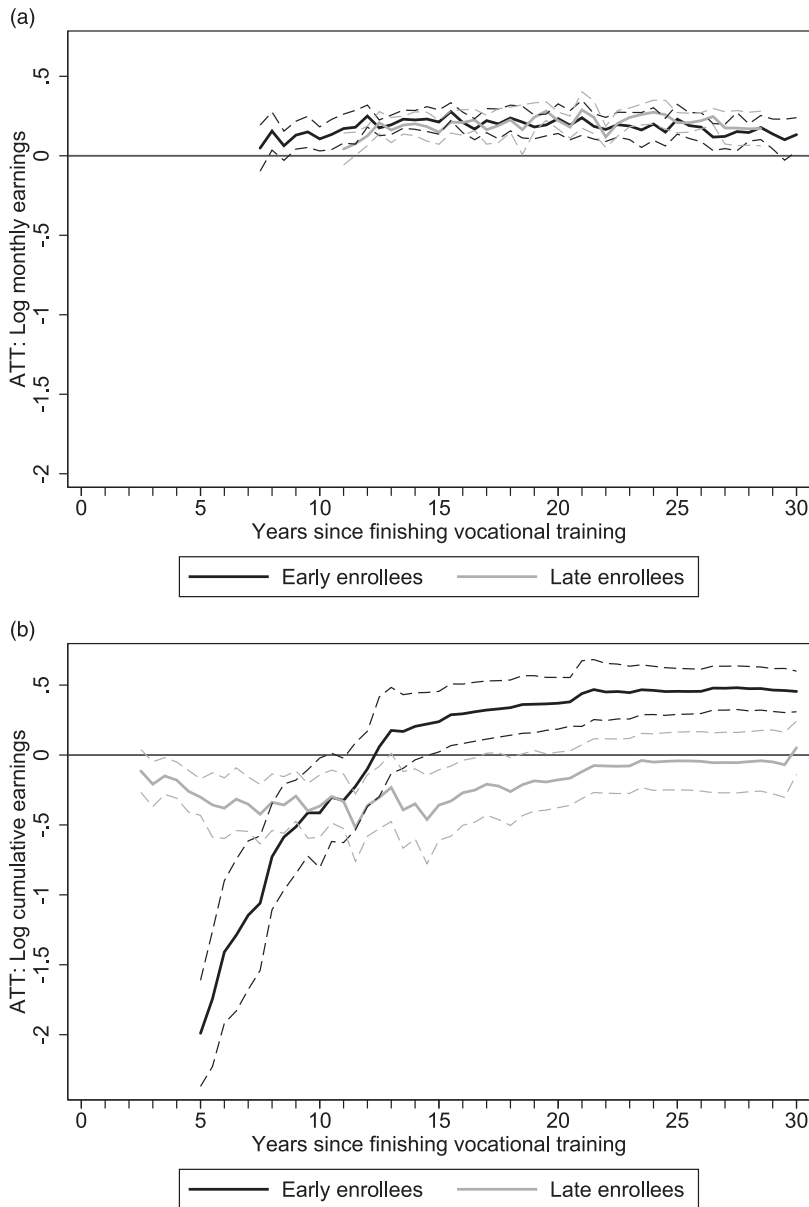


Figure 8. Average treatment effect on log monthly and cumulative earnings by enrollment timing. (a) Log monthly earnings, (b) Log cumulative earnings.

Notes: This figure displays the ATT for log cumulative earnings for early and late enrollees. The earnings are deflated to 2010 prices. The cumulative earnings are additionally discounted by a factor of 3%. The ATT is calculated using propensity score weighted linear regressions using a six-month time window. The point estimates shown are based on at least 25 treated observations. The standard errors are clustered at the federal state and vocational decade level. The dashed lines indicate the 95% confidence interval.

observation period, and possibly larger heterogeneity among the late enrollees than among the early enrollees.

This heterogeneity analysis provides suggestive evidence that returns depend on timing of enrollment. Enrolling in college based on vocational qualifications is more likely to pay off monetarily if done soon after finishing vocational training. However, the confidence intervals on the log

cumulative earnings are wide, hinting at a large variance in individual outcomes. Put differently, all enrollees face some risk in realizing higher earnings after the treatment.

3.4. Sensitivity analysis

Using the simulation-based method proposed by Ichino, Mealli, and Nannicini (2008), I assess the credibility of the CIA. One could expect that unobservable factors, such as ability and motivation, positively influence both the selection into treatment, i.e. college enrollment, and the labor market outcomes. If the conditioning variables do not capture these factors adequately, the results are biased and could not be interpreted causally. Therefore, I conduct a sensitivity analysis following Ichino, Mealli, and Nannicini (2008) and include a potentially unobserved confounder U into the set of conditioning variables.

Ichino, Mealli, and Nannicini (2008) define the following probabilities to describe the distribution of the potential confounder: $p_{ij} = \Pr(U = 1 \mid T = i, Y = j)$ where $i, j \in 0, 1$, T indicates treatment, and Y is the binary outcome. When covariates are binary, the p_{ij} correspond to the mean of the four groups determined by treatment (i) and outcome status (j).¹⁸ For example, if motivation were the confounding variable, p_{11} in my setting would provide the share of motivated who enroll in college based on vocational training and whose employment probability is above average. Ichino, Mealli, and Nannicini (2008) further distinguish between the ‘selection effect’ (s), i.e. the influence of U on T and the ‘outcome effect’ (d), i.e. the influence of U on Y .

To select meaningful values of p_{ij} for the potential confounder, I compute the p_{ij} for all conditioning variables.¹⁹ Most variables exhibit a selection effect of $s = 0.1$ and an outcome effect of $d = 0.1$. The median selection effect amounts to 0.04 for employment and MPS, and 0.01 for log cumulative earnings. The median outcome effect is 0.01 for employment and log cumulative earnings, and 0.04 for MPS. Of all variables, ‘male’ shows the largest combined effect of selection and outcome ($s = .35$ and $d = .28$) for employment as an outcome, and similarly so for MPS and earnings, though with lower values for s and d . This means, that men not only select more often into treatment, they are also more likely to be employed, i.e. to have a positive outcome. Therefore, I make use of the p_{ij} probabilities for ‘male’ to conduct the sensitivity check. Hence, by construction U is a very influential unobserved confounder.

Including such a confounder into the matching could attenuate the ATT because the differences in outcomes are now attributed to the treatment and not due to unobserved characteristics. Figures 9 to 12 confirm this intuition.²⁰ The ATT in these three outcomes are lower when including the simulated confounder into the matching.

The employment estimates are robust to including this influential potential confounder. Including the potential confounder U , the ATT is only modestly closer to zero. The effect on job prestige is remarkably attenuated but remains positive and significant. While the effects on log monthly earnings barely decline, the point estimates for log cumulative earnings are reduced somewhat more. Furthermore, the sensitivity check suggests that the positive effect on log cumulative earnings turns insignificant at the end of the observation period. This indicates that positive selection may explain the positive return, and reinforces the finding that while wage premiums are positive recouping the opportunity costs is not guaranteed.

All in all, this sensitivity analysis indicates that the main results are relatively robust to potential violations of the CIA. Including a very influential unobserved confounder merely attenuates the effect sizes, the main patterns remain the same. Only in the case of log cumulative earnings does the qualitative conclusion change since returns become insignificant when the potential confounder is included.

4. Conclusion

How can we ensure that today’s workforce meets tomorrow’s skill requirements? In the context of technological and demographic change currently challenging the German labor market, lifelong learning and substantial skill upgrades at later stages in life are increasingly important. Against this backdrop, this paper estimates labor market returns to college enrollment based on vocational

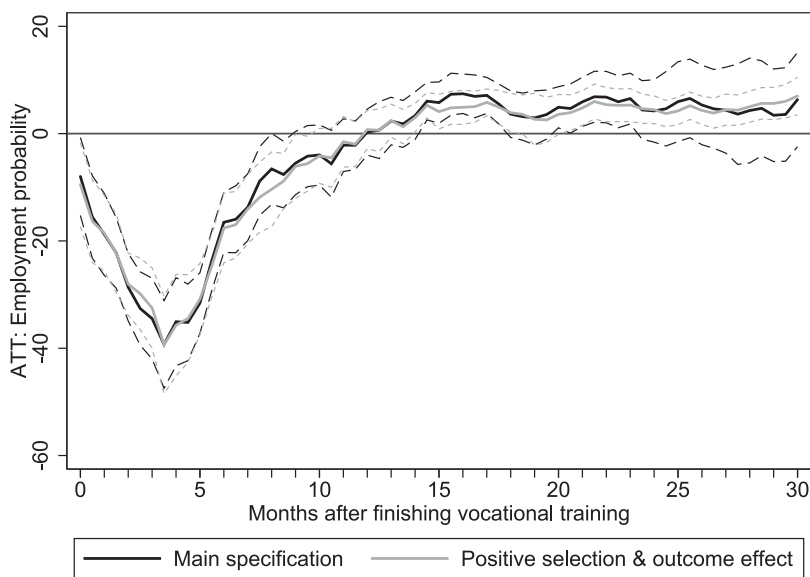


Figure 9. Sensitivity analysis for ATT for employment probability.

Notes: This figure replicates the results for the main specification for employment probability as an outcome, depicted in black. It also displays the results of the sensitivity analysis for this outcome, shown in gray, based on a simulation with 200 repetitions. The dashed lines show the 95% confidence interval. The simulated binary confounder mimics the effect of the variable ‘male’ in period 187, which has a positive selection effect $s = .34$ and a positive outcome effect $d = .28$.

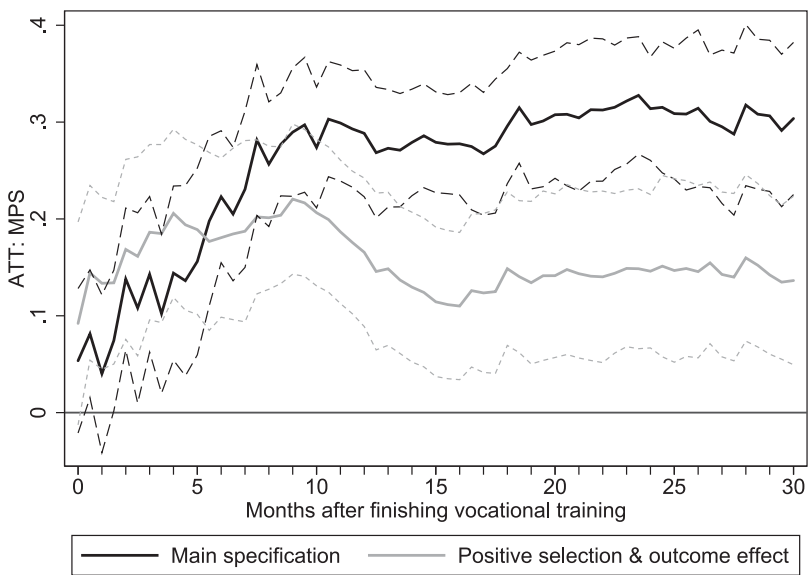


Figure 10. Sensitivity analysis for ATT for MPS.

Notes: This figure replicates the results for the main specification for MPS as an outcome transformed into a binary variable using the median as a threshold (black line). It also displays the results of the sensitivity analysis for this outcome (gray line) based on a simulation with 200 repetitions. The dashed lines show the 95% confidence interval. The simulated binary confounder mimics the effect of ‘male’ in period 187, which has a positive selection effect $s = .34$ and a positive outcome effect $d = .28$.

qualifications, one policy promoted by the German Education Minister Conference. Using the NEPS, I identify individuals who took this path in the past and compare them to those who continue with a typical vocational-training-based career relying on propensity-score-adjusted regressions.

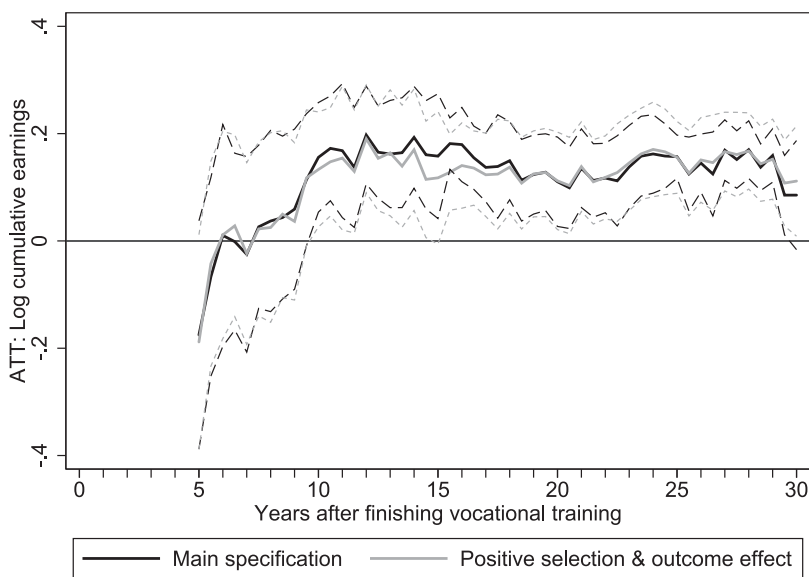


Figure 11. Sensitivity analysis for ATT for log monthly earnings.

Notes: This figure replicates the results for the main specification for log monthly earnings as binary outcomes transformed using the median as a threshold (black line). It also displays the results of the sensitivity analysis for these outcomes (gray line) based on a simulation with 200 repetitions. The dashed lines show the 95% confidence interval. The simulated binary confounder mimics the effect of ‘male’ in period 187, which has a positive selection effect $s = .34$ and a positive outcome effect $d = .28$.

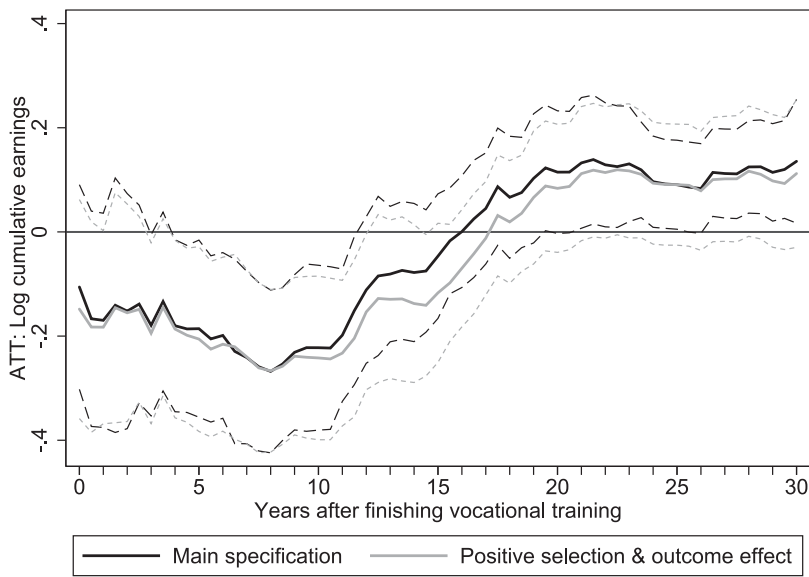


Figure 12. Sensitivity analysis for ATT for log cumulative earnings.

Notes: This figure replicates the results for the main specification for log cumulative earnings as binary outcomes transformed using the median as a threshold (black line). It also displays the results of the sensitivity analysis for these outcomes (gray line) based on a simulation with 200 repetitions. The dashed lines show the 95% confidence interval. The simulated binary confounder mimics the effect of ‘male’ in period 187, which has a positive selection effect $s = .34$ and a positive outcome effect $d = .28$.

The results show that labor market returns to enrolling in college based on vocational qualifications vary across career phases. While high opportunity costs characterize the early phase, returns tend to become more positive as the career progresses. For instance, enrollees have much lower employment

levels during the early phase of the career than those who continue with their vocational-training-based career. In the long-run, they exhibit similar employment levels as the control group. However, there seems to be a high degree of uncertainty with respect to the monetary returns, especially the cumulative earnings. While the wage premiums turn positive about 10 years after finishing vocational training, opportunity costs of enrolling are high and take a very long time to recoup. Only about 20 years after finishing vocational training do enrollees accumulate about the same level of earnings as the control group. At the end of the 30-year observation period their cumulative earnings are positive albeit on the verge of insignificance and with wide confidence intervals. This indicates that recouping the opportunity costs of enrolling in college is a lengthy and uncertain process. Furthermore, after finishing college, enrollees obtain jobs with a higher societal reputation than the control group. Enrollees take up occupations which score up to 35 points higher on the MPS, which spans from 20 to 186.8. This suggests that there may be considerable non-monetary returns to enrolling in college based on vocational training, which are more certain than the monetary returns.

In a heterogeneity check, I take timing of treatment into account and show that any long-run, positive monetary returns are associated with those who enroll in college soon after finishing vocational training. Those who enroll later do not recover the opportunity costs during the study's observation period. Furthermore, the sensitivity analysis confirms the estimated patterns of most outcome variables, except for log cumulative earnings. The results for log cumulative earnings appear particularly prone to vanish if there is positive selection into treatment.

There are a few limitations to this analysis. First, the data do not allow investigating complete labor market histories. As treated individuals age, they may reap more benefits such as higher old-age labor market attachment or higher life-time earnings. Second, the estimated returns may not fully carry over to returns of enrolling in college based on vocational qualifications today since recently the college-premium has fallen somewhat in Germany (Crivellaro 2016). Hence, in this respect the results of this paper may represent an upper bound.

In sum, this paper suggests that individual monetary returns to opening colleges to the vocationally qualified are not definitely positive. Yet, there may be sizable non-monetary returns associated with having access to different kinds of occupations after enrolling in college. From a policy perspective, earlier upgrades from the vocational to the academic track, e.g. just after lower secondary school, seem to be more likely to produce positive monetary returns (Dustmann, Puhani, and Schönberg 2017). Alternatively, after vocational training, it may be more lucrative to continue with further training on the vocational track since there is evidence that advanced vocational degrees such as a Master of Craftsman render high monetary returns (Lauer and Steiner 2000).

Notes

1. In absolute numbers, 3438 individuals enrolled based on vocational qualifications in 2003 and 13,215 in 2013 (Federal Statistical Office 2015b). By comparison, about 286,000 and 453,000 individuals aged 20–30 in the German labor market in 2003 and 2013, respectively, had completed a substantial further training and many of these would therefore have qualified for college studies based on their vocational credentials (Federal Statistical Office 2005, 2014).
2. College refers to all tertiary education institutions that traditionally require a form of the German high school leaving certificate, the so-called *Abitur*, i.e. universities, universities of applied sciences, and university of cooperative education.
3. This estimation used data on locations and opening dates from Spiess and Wrohlich (2010). These results are available on request.
4. There are 44 clusters.
5. I use the weakly anonymous NEPS: Starting Cohort 6 - Adults (Adult Education and Lifelong Learning), doi:10.5157/NEPS:SC6:5.1.0. The NEPS data was collected as part of the Framework Program for the Promotion of Empirical Educational Research funded by the German Federal Ministry of Education and Research (BMBF) from 2008 to 2013. As of 2014, NEPS is carried out by the Leibniz Institute for Educational Trajectories (LifBi) at the University of Bamberg in cooperation with a nationwide network.
6. The German Record Linkage Center (GRLC) linked the NEPS data to the Integrated Employment Biographies. Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and remote data access.

7. The median deviations of the ATT estimated based on the NEPS-ADIAB sample compared to the NEPS sample are 2 percentage points, 0.5 percentage points, and 1 points on the Magnitude Prestige Scale for employment probability, full-time employment probability and job prestige, respectively. These deviations lie by and large within the confidence interval of ATTs estimated using the NEPS sample. Results available upon request.
8. The categories of inconsistencies are: being younger than 11 at a *Hauptschulabschluss* or higher, being younger than 12 at a *Mittlere Reife*, being younger than 14 when starting vocational training, being younger than 20 when obtaining a *Meister*, younger than 20 when finishing a college degree, enrolling in tertiary education 6 months before finishing secondary school or prior to finishing vocational education. Furthermore, I do not include individuals in the sample who are 40 years or older when starting a college degree since one cannot observe enough labor market episodes after the treatment.
9. Only for the 1950/60s and 1970s vocational training cohort, the oldest in the sample, could one observe the labor market outcomes for longer than 30 years. However, I am interested in an average effect; therefore, I limit the observation period to ensure a reasonable amount of treated and control group observations for each point in the labor market history time line.
10. This variable is constructed using the Biography sub-dataset in the NEPS. Whenever an individual indicates having an employment spell (sptype=26) the indicator turns 1 but subtracts those who indicate being self-employed.
11. I use the MPS since this is a national measure and therefore captures the German occupational landscape better than measures constructed using international scales such as the socioeconomic index of occupational status (SIOPS) (Christoph 2005).
12. If there were parallel employment spells the ISCO or MPS information was taken from the job with a) the most hours, b) the longest spell duration (for those who still have parallel spells after a) and c) the highest MPS (for those who still have parallel spells after a and b).
13. Reichelt (2015) proposes to predict wages above the top-coded income level based on interval regressions with the following covariates: schooling, age, sex, 3-digit occupations, job position, size of firm, and an East Germany indicator.
14. In the NEPS-ADIAB sample 1:40 nearest neighbor matching with a caliper of .0076 performs best.
15. I calculate the returns per year by dividing the overall returns by 3.25, which is the average duration in college in years.
16. Vocational and college occupational information is available for 82% of the treated. The occupational segments are characterized by easy within-mobility and thus represent more homogeneous occupation groups than alternative occupational classifications such as the ISCO code (Matthes, Burkert, and Biersack 2008).
17. In the balancing tests for the propensity score matching for the early and late enrollees the mean bias also mostly lies below the 5% benchmark value. These results are available upon request.
18. Using the mean as a threshold, I transform continuous covariates into binary variables as Nannicini (2007) suggests.
19. I calculate these probabilities for outcomes 15.5 years after vocational training, since this lies in the middle of the observation period. The results are available upon request.
20. I adapt the `sensatt.ado` provided by Nannicini (2007) to the setting of propensity score-weighted regressions.

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