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ABSTRACT

Labor-Market Returns to Higher Vocational Schooling*

This paper examines the labor-market returns to a new form of postsecondary vocational education, vocational master's degrees. We use individual fixed effects models on the matched sample of students and non-students from Finland to capture any time-invariant differences across individuals. Attendance in vocational master's programs leads to higher earnings of eight percent five years after entry even if selection on unobservables is twice as strong as selection on observables. Earnings gains are similar by gender and age, but they are marginally higher for health than for business or technology and trades.

JEL Classification: J24, I26

Keywords: vocational education, master's degrees, labor-market returns

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1. Introduction

Vocational skills are valued in the labor market. Along with academic qualifications, the demand for work-oriented vocational skills is increasing (ILO, 2011). Policy makers have responded to the call to improve and enhance the content of vocational education and training. The European Union initiated the Bruges Communiqué in 2010. It describes a roadmap for vocational education and training in Europe 2020. In the policy document, practical work-oriented vocational skills are treated as important as academic qualifications (Brunello and Rocco, 2015).

In this paper, we analyze the labor-market returns to a new breed of postsecondary vocational education that combines the development of work-oriented vocational skills with updating of academic knowledge. Deeper understanding of the connection between vocationally-oriented education and labor market outcomes is central to design education policies, because a better match between skills and work promotes more inclusive labor markets (OECD, 2017). Countries around the world are considering how to allocate resources between universities and vocational tertiary education providers in order to best support their citizens and economies.

The majority of studies on the labor-market returns to postsecondary vocational education focus on bachelor’s level or lower-level programs. Recent evidence for the U.S. shows that community college degrees and diplomas in vocational areas lead to higher earnings and employment, particularly for women (see Jepsen, Troske, and Coomes (2014), Belfield and Bailey (2017), and the references therein). These programs are both vocationally- and academically-oriented and require up to two years of full-time study. In

Europe, many vocational programs are of longer duration, up to four years, and culminate in the receipt of a vocational university degree.[1]

Little if anything is known about the potential labor-market returns to master's degrees with a vocational focus even though several European countries such as Germany, Portugal, and Finland offer such degrees. The growing literature on postgraduate education completed later in life focuses narrowly on academic degrees (Hällsten, 2012; Stenberg and Westerlund, 2016). Rapid technological change is occurring in occupations and industries such as manufacturing where workers traditionally have vocational rather than academic education. Lifelong learning, either in the form of on-the-job training or in terms of formal education, is vital for workers to succeed in these jobs. For example, over 60 percent of U.S. workers have received training or instruction at work in the last 12 months (Horrigan, 2016). Analysis of those who have prior working experience is especially policy-relevant in the aftermath of the global economic crisis, because many unemployed have to decide whether to pursue additional schooling, and the government has to decide whether to invest more resources in higher vocational education to improve labor-market outcomes of young people.

This paper contains the first estimates (of which we are aware) of the labor-market returns to schooling in new vocational master's programs that were established in 2002. We examine returns to formal part-time education for prime-age workers (aged 25 to 55 at entry). Using complete annual register data from Finland, we first create a matched comparison sample of individuals who would be eligible to attend vocational master's programs in polytechnics, have similar demographic characteristics, ability, and pre-master's-enrollment labor-market experiences, but choose not to attend. On this matched sample of students and non-students, we estimate an individual fixed effects model to compare earnings before and

[1] Dearden et al. (2002) analyze variety of academic and (lower level) vocational qualifications in the U.K. They find that the wage premium associated with academic qualifications is typically higher than the premium associated with vocational qualifications at the same level. For Finland, Böckerman, Haapanen, and Jepsen (2018) find sizable positive earnings and employment impacts for attending polytechnic *bachelor's* degrees; see also Böckerman, Hämäläinen, and Uusitalo (2009).

after attending vocational master's programs. We estimate models of attendance and models of completion.

Results from the individual fixed effects models show that individuals who attend vocational master's programs – whether or not they complete a degree – have higher earnings than a matched comparison group who do not attend. By five to six years after entry, the earnings gains for attendees are approximately 8 percent of the average earnings in the year before entry. Over the same time period, the returns to degree completion are higher, around 11 percent. Returns are broadly similar between males and females and between younger and older students. Five to six years after entry, students from health have the highest returns, followed by technology and trades. All our estimates remain robust even if there is substantial positive selection into vocational master's programs. Because most European countries, like Finland, have vocational bachelor's programs enrolling large numbers of students, these findings demonstrate the potential earnings benefits for further expanding vocational education to the master's level.

2. Vocational Master's Program in Finland

The Finnish government created polytechnics in 1991 to provide higher-level vocational education. Polytechnics are public institutions and an integral part of the education system.[2] The funding of the polytechnics is provided by the state and local authorities. Polytechnics offer bachelor's degrees that take approximately 3.5 to 4 years of full-time study. By the end of 2001, around 61,000 students had completed these bachelor's degrees in Finland, but they had very limited opportunities for acquiring further formal education in university master's programs. Starting in 2002, the government began a three-year trial period where 20 polytechnics were allowed to run six different polytechnic master's

[2] See Böckerman, Haapanen, and Jepsen (2018) and references therein for further information on vocational bachelor's degrees in Finland. Supplementary Online Appendix C (Figure C1) provides an illustration of the Finnish education system before and after the second phase of the polytechnic reform in 2002.

programs ("*ylempi* AMK" in Finnish), with aggregate enrollment of 300 students per year. Licenses for these programs were issued by the Ministry of Education.

During the initial trial period, there were only programs in business and administration, social welfare and health care, and technology and trades (such as construction). They were regarded as fields that transform and internationalize rapidly and therefore require life-long learning and continual upgrading of practical work-oriented skills. Later programs covering other major fields were also added. There were 1,312 applicants for the polytechnic master's programs in 2002–2004 (in the end, 900 applicants were accepted and 706 students began in the polytechnic master's programs). During the first application round, the programs on entrepreneurship and business skills for small and medium enterprises (SMEs), social work as well as health promotion and preventative health care were the most popular.

Eligible criteria for enrollment in a polytechnic master's program are completion of a polytechnic bachelor's degree (or other applicable degree) and a minimum of three years of work experience in the relevant field prior to entry. During the trial period, the work experience had to be accumulated after completion of the bachelor's degree. After 2005, part of the work experience could also be accumulated before the bachelor's degree (minimum one year of work experience after the bachelor's degree).[3] We account for work experience with a comprehensive set of register-based controls (e.g. employment and earnings history, and pre-treatment enrolment in education programs).

Because the trial period was deemed successful, polytechnic master's programs have expanded substantially. For example, nearly 2,000 new students entered these programs in 2008 and around 4,300 students in 2016. As a consequence of this expansion, master's degrees can be completed in two parallel sectors offering separate schooling tracks:

[3] Due to the small number of entrants during the trial period we cannot exploit this policy change.

universities engaged in academic research and vocationally-oriented polytechnics. Some subjects are offered in polytechnics, but not in universities, and *vice versa*. Contrary to a university master's degree, a polytechnic master's degree does not provide academic qualifications for studies in doctoral programs.

In Finland, the new polytechnic master's degree programs take from one to one and a half years of full-time study to complete (60–90 ECTS[4] credits; around 72–108 ECTS credits during the trial period). In practice, the programs are designed for completion in two to three years of part-time attendance. Contrary to university education (or the polytechnic bachelor's degrees), the polytechnic master's degree programs are organized in a way that studying is possible while working at the same time (Ministry of Education and Culture, 2012). Teaching modes include contact days, independent work, and utilizing online-learning environments. Lectures are mostly given on Fridays and Saturdays and in the evenings. A significant part of the degree is to write a thesis (30 ECTS credits), which is often a development project closely linked to the needs of the current employer (Ministry of Education and Culture, 2012). Echoing findings for those of UK students on similar programs (Pratt et al., 1999), few students start a polytechnic master's program with the explicit intention to move to a new job. Instead, most students seek to improve their professional knowledge, skills and understanding in their current employment (Pratt et al., 2004).

The central purpose of these programs is to offer further training in vocational skills that are closely relevant to the labor market.[5] Another aim is to provide sufficient knowledge and skills for demanding expert and leadership positions, and continuous development of working-life tasks. Studying is free, and students are entitled to (income-dependent) study grants.

[4] ECTS = European Credit Transfer and Accumulation System.

[5] On-the-job training does not lead to formal degrees, and it is only offered by the largest manufacturing firms in Finland. Administrative data do not record on-the-job training.

The Finnish polytechnics resemble *Fachhochschulen* in Austria, Germany, and Switzerland, *Hautes écoles* in French in Belgium and Switzerland, *Hogescholen* in the Netherlands, and *Escolas Politécnicas* in Portugal that also offer both bachelor's and master's level qualifications with vocational (professional) emphasis (OECD, 2014). To some extent, the post-initial *Hoger Beroepsonderwijs* (HBO) in the Netherlands and the part-time professionally oriented master's degrees in Britain are also similar to those in Finnish polytechnics (Pratt et al., 2004: p. 42). Contrary to Finland, these students in the Netherlands and Britain, however, need to pay tuition fees. A unique feature of the Finnish polytechnic master's programs is that they combine adult education and lifelong learning with the structure of a formal degree program organized around and focused upon a research project undertaken by the student in a work-related situation (Pratt et al., 2004: p. 23).

3. Data

In the empirical analysis, we utilize exceptionally rich registry data on the total population of Finland. The basic individual-level data come from the Longitudinal Population Census Files and the Longitudinal Employment Statistics Files constructed by Statistics Finland. These two administrative data sets were updated on five-year intervals from 1970 to 1985 and annually from 1987 to 2014. The data contain all under 70-year-old individuals in Finland during this period, with the exception of individuals who live or attend polytechnics in the Åland Islands, an area with many linguistic, cultural, and geographic differences from the rest of Finland. The data are further merged with the Registry of Completed Degrees, which holds information on completed degrees since 1970, and the Registry of Student Population, which contains information on attendance at degree-leading educational programs since 1995. Finally, the data are linked to comprehensive data on all high-school matriculation exam scores since 1967. Because individuals are matched based on their unique personal identifiers across time periods and data sources, these panel data sets provide a variety of reliable, register-based information on *all* the residents of Finland including data on spouses and parents.

We limit the sample of potential entrants of polytechnic master's programs to people with polytechnic bachelor's degrees as their previous qualification by 2008, because over 95 percent of attendees have a polytechnic bachelor's degree. From the sample we also exclude the small number of students who enter the master's degree programs under age 25 or over age 55 to have sufficient number of labor market observations before and after the treatment.[6] We also exclude the relatively few students who have moved abroad during the study period. After these exclusions, we are left with 175,350 polytechnic bachelor's recipients.

The sample is divided to treated and control groups. The treatment group consists of 7,148 individuals who enter a (first) polytechnic master's program in 2002–2009. Entrants in 2010 or later are excluded because they do not have sufficient post-schooling earnings data to study the labor-market returns. Of the polytechnic master's students, 71.0% complete their studies by 2014. The polytechnic master's students are compared to 168,202 polytechnic bachelor's recipients with no attendance in the polytechnic master's programs by 2014.

Treatment and control groups contain small number of individuals (~5%) who attend universities. However, our main results are not sensitive to the inclusion or exclusion of the university students in the data (cf. Table 2 and Table B5). In the analyses, all individuals are followed for a maximum of ten years backward or age 18, and a maximum of eight years[7] forward until 2014 or age 64 (normal retirement age).

4. Method

Our preferred method utilizes two important features of the data: the availability of data on entrants and non-entrants along with panel data for many years. We combine these

[6] See Supplementary Online Appendix (Figure C2) for the distribution of age at entry to polytechnic master's programs.
[7] We do not estimate treatment effects for $t > 8$ because of the low number of observations for these periods (few individuals started their studies in 2002–2004).

two features by estimating fixed effects models on the matched sample of entrants and non-entrants.

4.1 Matching Model

We use detailed register data to identify a comparison group that has no vocational master's schooling but has nearly identical likelihoods of attending vocational master's programs based on pre-schooling characteristics such as demographics, earnings, and employment. Denoting the year of attendance, or the year of the attendance decision, as t, the potential control group consists of individuals who have completed a polytechnic bachelor's degree by year $t-1$ but have not attended or graduated from any additional postsecondary education (including a polytechnic master's program). For example, an individual with bachelor's degree from 1998 (who does not enter polytechnic master's programs in the future) can act as a control for program entrants in 2002, 2003, …, 2009. Thus, this control individual appears eight times in the unmatched data.[8]

We calculate the likelihood of attending a vocational master's program – for a pooled sample of people who enter the program and people who do not – as follows:

(1) $AttendMA_i = f\left(X_{i,t-s}, Y_{i,t-j}\right),\ j = 0, 1, \ldots, 10,\ s > 0,$

$AttendMA_i$ is a dichotomous variable equal to 1 for individual i who enrolls in time t for the first time in the program. $X_{i,t-s}$ is a set of explanatory variables as shown in Table A1, measured before the enrollment decision ($t-1$ or earlier). In addition to measures of prior employment and earnings, these explanatory variables include measures of ability (measured in secondary school), bachelor's degree characteristics such as the field of study, family demographics, and parental education and occupation.[9]

[8] In total, 168,202 control individuals generate 766,405 potential control observations that are matched with the 7,148 treated individuals. As result of propensity score matching, out of the 12,984 matched control individuals, 835 (49, 2) are matched twice (three, four times) with the treated individuals.
[9] Blundell et al. (2005) stress the importance of correcting for test score and family background differences to estimate the labor-market returns to education. In our specifications, we interact some variables with each other. For example, household characteristics are interacted by gender.

The decision whether or not to include earnings and employment from the year of enrollment (for polytechnic master's students) is not clear. Nearly all students are working in the year t in which they begin their master's program. Because most programs start in August or September, most of the annual earnings in the enrollment year occurs before the student enrolled. Thus, excluding earnings in year t ignores some pre-enrollment earnings, but including earnings in year t may have endogeneity concerns by matching on a post-enrollment outcome. We check the sensitivity of this assumption by matching individuals with two models, one that includes earnings in t as a control and one that excludes earnings in t as a control.

We use propensity score matching based on the two nearest neighbors, but our results are robust to using either coarsened exact matching or inverse probability weighting.[10] Using an individual who enters a polytechnic master's program in 2006 as an example, we compare the entrant with the two control individuals (non-entrants) with the most similar entry probabilities based on pre-treatment demographic characteristics and employment and earnings from 1996 to 2005 (or 2006). We match with replacement, implying that an individual with no vocational master's attendance can be matched with more than one entrant in the same year. With this matched sample (two control observations and one treatment observation), we compare the average earnings and employment development among entrant and non-entrant groups from ten years before up to eight years after the entry decision.

The matching method assumes that all selection between vocational master's students and individuals who do not attend is on observables and therefore is captured by the propensity score. Because prior register-based earnings and employment, along with high-

[10] Specifically, we have estimated the matching models using coarsened exact matching (Iacus et al. 2012). These CEM results are reported in Supplementary Online Appendix A (Table A4 and Figure A4). The CEM and inverse probability weighted (IPW) fixed effects regression results are shown in Figures B1 and B2 (Appendix B). In all cases, the results are qualitatively similar to our preferred matched fixed effects results based on nearest-neighbor matching.

school matriculation exam scores, are very informative predictors of future labor-market outcome, combined with the entry requirement of at least three years of earnings prior to entering a vocational master's program, the selection-on-observables assumption has merit. Matching estimators based on prior earnings are common in studies of job-training; for example, see Heinrich et al. (2013). One key advantage of matching is that allows us to test the covariate balance between the entrants and non-entrants after implementing the method. For each covariate, we report the standardized percentage bias as well as the variance ratio to compare the distribution of covariates between treatment groups as recommended by Austin (2009); see Supplementary Online Appendix A (Table A3).

4.2 Individual Fixed Effects Models on the Matched Sample

On this combined sample of entrants and the matched comparison group of non-entrants, we also estimate individual fixed effects model. This model has been used extensively to study the returns to schooling literature (Jacobson, LaLonde, and Sullivan, 2005a, 2005b; Jepsen, Troske, and Coomes, 2014; Cellini and Chaudhary, 2014; Cellini and Turner, 2016; Jepsen, Mueser, and Jeon, 2016).

The fixed effects model shown in equation (2) estimates the returns to attendance:

$$(2) \qquad Y_{it} = \beta_{1t} AttendMA_i \times TIME_t + \beta_{0t} TIME_t + \alpha AGE_{it} + \tau YEAR_{it} + \eta_i + \varepsilon_{it}$$

The dependent variables (Y_{it}) are annual measures of earnings and employment for individual i in time t. Our preferred earnings measure is total annual earnings measured in 2012 euros (using the consumer price index).[11] Employment is measured as a dichotomous variable equal to one for individuals who are employed during the last week of each year.

To allow as much flexibility as possible, $TIME_t$ is simply a set of dichotomous variables measuring the number of years since enrollment. In order to compare the earnings of entrants with the matched set of non-entrants, we also include interaction terms between

[11] Our results remain similar when using log earnings as the dependent variable.

the treatment group (i.e. attending polytechnic master's programs) and this set of dichotomous variables: $AttendMA_i \times TIME_t$.[12] These interaction terms are the coefficients of interest because they capture the extra increase (or decrease) in earnings for individuals who attend polytechnic master's programs relative to the matched sample of workers who do not enroll in master's programs. Because the year before enrollment is the omitted year, the coefficients for each time period capture the gain (or loss) in earnings or employment relative to the year before starting the polytechnic master's program. *AGE* includes dummy variables for each year of age, measured in the year of observation, to allow for the flexible age-earnings profiles. The model also includes *YEAR* effects (τ), measured as a set of dichotomous variables for each calendar year, in order to capture differences in macroeconomic conditions such as recessions.

The individual fixed effects (η) control for time-invariant measures of ability and personal characteristics that affect earnings and are correlated with polytechnic master's programs. The fixed effects approach assumes that the pre-schooling and post-schooling earnings and employment patterns are similar between students who attended a master's degree program and the matched comparison sample of those who did not. If a student receives a positive or negative shock that affects degree receipt / attendance and earnings patterns, the fixed effects model will not produce valid estimates. The last term in equation (2), ε, is the unobservable component of earnings and employment. There are up to 19 years for each individual, from 1992 to 2014. Standard errors are clustered at the person level to account for unobservable, within-person variation in outcomes.

A salient feature of the data is that we have multiple cohorts of entrants, i.e. students who enter polytechnic master's programs over several years. Given this variation in entry times, coupled with the time effects for calendar year, coefficients β_{1t} capture the changes in

[12] Jepsen, Mueser, and Jeon (2016) use a similar model to estimate returns to proprietary schooling in the U.S. using quarterly data, except that they only have data for students. Therefore, they are unable to include interaction terms between the treatment group and time since enrollment.

labor-market outcomes net of differences in age-earnings profiles. These profiles are captured by the time fixed effects and the controls for age.

Many papers in the returns to vocational schooling literature attempt to estimate the returns to degrees as well as returns to attendance (e.g. Cellini and Chaudhary, 2014). We estimate two specifications that differ in how we model the returns to degree completion. The model in equation (3) includes an additional coefficient, *PostDegree*, which is a dichotomous variable equal to one for polytechnic master's (MA) degree recipients in the time periods after the receipt of an MA degree:

$$(3) \qquad Y_{it} = \beta_{1t} AttendMA_i \times TIME_t + \beta_{0t} TIME_t + \lambda PostDegree_{it} + \alpha AGE_{it} + \tau YEAR_{it} + \eta_i + \varepsilon_{it}$$

The dependent variables Y are the same as in equation (2), the annual measures of earnings and employment, as are the measures of the returns to attendance: $AttendMA_i \times TIME_t$.

In equation (3), $PostDegree$ is a dichotomous variable for having a polytechnic master's degree in the beginning of the year t. For example, a person who received a degree in 2007 will have values of 0 until 2007 and values of 1 from 2008 on. For individuals who never receive a degree, $PostDegree$ has values of 0 in all periods. In this specification, we assume that the returns to degree completion are time invariant and are equal to the coefficient in $PostDegree$ for each time period after completion.

In the final specification, we model the returns to completion by running separate regressions for completers (and their matched comparison group members) and dropouts (and their matched comparison group members). This specification allows for the returns to degree completion to vary across time, as well as allowing for different pre-enrollment trends in earnings between completers and dropouts. We use separate models so that the returns for completers (dropouts) can be easily compared to their matched counterparts. Because the second completion model is more flexible, it is our preferred specification for estimating returns to degree completion. In interpreting estimates of both models, caution is required as degree completion is endogenous.

In summary, the fixed effects methods combined with matching utilize the unique feature of the vocational master's programs requiring students to have at least three years of work experience in the field in which they plan to pursue post-graduate studies (see Section 2). Both the matching models and fixed effects models are based on the assumption that the pre-enrollment earnings and employment trends for vocational master's students are meaningful measures of their labor-market outcomes in the absence of further education. Due to the work-requirement of master's programs, we argue that these models are more appropriately used in a study of vocational master's programs than in previous studies of the returns to community colleges, for-profit colleges, and vocational bachelor's programs.

5. Results

5.1 Matching Quality

Table 1 provides descriptive statistics for three samples: the set of polytechnic master's students (i.e. the treatment group), and the entire population of polytechnic bachelor's recipients who do not pursue vocational master's degrees (i.e. the control group), the subset of "non-students" who are matched with vocational master's students (i.e. the "matched control group"); Tables A2 and A3 provide additional statistics of the matching quality.

Table 1 – Descriptive Statistics: Treated vs. Unmatched and Matched Control Observations (Selected Variables)

	(1)	(2)	(3)	(4)	(5)
	Entrants	Non-Entrants (Unmatched)		Non-Entrants (Matched)	
	Mean	Mean	% bias	Mean	% bias
Earnings at t - 3	32.017	21.968	65.7	28.427	-0.1
Earnings at t - 2	34.674	25.061	61.7	31.957	0.4
Earnings at t - 1	36.806	28.055	54.6	34.750	-0.5
Earnings at t	38.185	30.133	48.6	36.870	-0.4
Employed at t - 3	0.956	0.783	52.9	0.959	-1.2
Employed at t - 2	0.969	0.843	44.0	0.971	-0.7
Employed at t - 1	0.975	0.888	35.0	0.978	-0.9
Age in years	36.614	32.818	53.3	36.650	-0.5
Female	0.631	0.614	3.6	0.632	-0.3
Finnish speaker	0.963	0.955	4.0	0.964	-0.7
Swedish speaker	0.025	0.033	-5.3	0.024	0.4
Other language	0.013	0.012	0.9	0.012	0.7
Not living in the region of birth	0.445	0.428	3.4	0.448	-0.7
Enrolled in any education, t - 1	0.066	0.068	-0.7	0.059	2.8
Enrolled in any education, t - 2	0.113	0.220	-28.8	0.104	2.5
Enrolled in university education, t - 1	0.017	0.008	8.2	0.016	1.1
Enrolled in university education, t - 2	0.021	0.009	9.5	0.021	-0.2
BA-degree from business	0.257	0.282	-5.7	0.260	-0.8
BA-degree from tech & trades	0.259	0.272	-2.8	0.254	1.3
BA-degree from health care	0.347	0.288	12.5	0.347	0.0
BA-degree from other fields	0.137	0.158	-5.8	0.139	-0.7
Years from BA-degree to entry	5.562	4.462	41.5	5.644	-3.1
Comprehensive school grade (4–10)[a]	7.965	7.944	2.8	7.962	0.4
Has graduated from high school	0.701	0.734	-7.4	0.709	-1.6
Exam score in native language					
Not written or failed	0.289	0.259	6.9	0.281	1.7
1	0.029	0.035	-3.3	0.028	0.3
2	0.103	0.107	-1.3	0.103	-0.1
3	0.262	0.286	-5.4	0.266	-1.1
4	0.227	0.223	1.0	0.235	-1.7
5	0.090	0.091	-0.2	0.086	1.4
Married	0.812	0.738	17.8	0.810	0.5
Has child	0.302	0.318	-3.5	0.304	-0.5
Unempl. rate	0.098	0.103	-12.1	0.098	0.0
Living in Helsinki region	0.292	0.323	-6.8	0.295	-0.7
Number of observations	7,148	766,405		13,923	

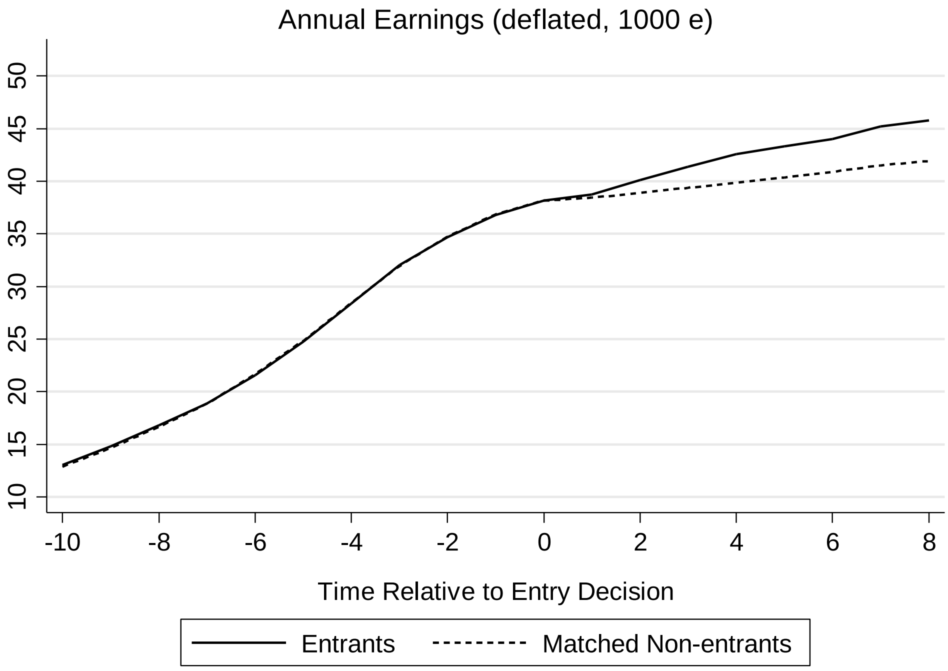
Notes: Percentage biases have been standardized by sample variances. Earnings are measured in 1,000 euro (deflated to 2012). See Tables A1, A2, and A3 for complete list of control variables and their descriptive statistics. These variables include number of degree-leading education programs attended in 7 years, study loan, comprehensive school grade missing, exam score in English language and mathematics, and spouse's and parents' characteristics. Data also include dummies for region of residence prior to entry (NUTS-3) and entry year. [a] Conditional on the availability of the school grade.

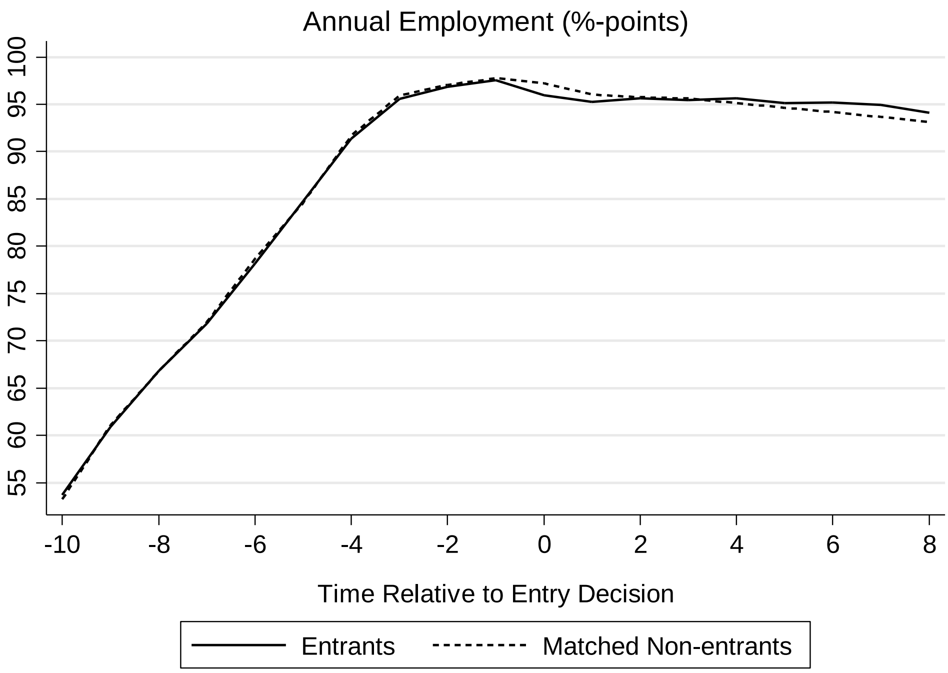
A comparison of column (1) and column (2) shows that vocational master's students have several differences from the population of polytechnic bachelor's recipients. For example, master's students have higher pre-enrollment earnings[13] and employment, but fairly similar measures of ability, compared to the full population of bachelor's recipients. However, a comparison of columns (1) and (3) shows that, as expected, the subset of polytechnic bachelor's recipients who have been matched with polytechnic master's students have similar characteristics – in the pre-enrollment period – to the master's students. Based on standardized differences in means, covariates are well balanced between the matched entrants and the non-entrants. Table A3 shows that the variance ratios of treated over matched non-treated are close to one, which shows good balance for continuous covariates.

Figure 1 illustrates the pre- and post-treatment trends in earnings and employment for the matched control group and the treatment group.[14] Contrary to previous literature on the displaced workers (Jacobson, LaLonde, and Sullivan, 2005a, 2005b), we do not find an Ashenfelter dip in earnings prior to entry (for the entrants). There are two reasons for this finding. First, our data are measured on annual basis, whereas the U.S. studies use quarterly data. Second, the polytechnic master's students are almost always employed before and after the entry to education. Vocational master's students have higher post-treatment earnings than the matched sample of non-students. For employment, the post-treatment differences are less pronounced. This observation is as expected given the high pre-treatment employment levels in excess of 95 percent for vocational master's students. Students have a small dip in the employment rates during the enrollment to master's programs.

[13] Earnings are in 2012 euros, deflated by the consumer price index.
[14] See Supplementary Online Appendix A for the full matching results. Additionally, Figure C3 in the Appendix C illustrates the development of earnings and employment before and after the entry for the full control group and the treatment group.

Figure 1 – Development of Labor Market Outcomes for the Treated and Matched Control Group





Notes: A probit model is used to estimate the propensity scores (see Table A1 for results). Individuals are followed backwards until age 18.

5.3 Fixed Effects Regression Results on the Matched Sample

Figure 2 and Table 2 contain the results from the fixed effects model for attendance. The top panel of the figure and the first columns of the table report results where the dependent variable is total annual earnings. In the bottom panel of the figure and the last two columns of the table, the dependent variable is annual employment. Specifically, we report the gain (or loss) in earnings associated with attending a master's program relative to the time period one year prior to entry in the master's program, the omitted time period in the regressions. In addition to these interaction terms between time and attendance, the model also contains dummy variables for the time period relative to attendance to control for overall trends in earnings for the combined sample of attendees (treatment group) and the matched control group.

Figure 2 shows that annual earnings for program attendees are approximately €380 higher than for the control group in the year after entry compared to the year before entry. This increase in earnings while most attendees are still enrolled may be due to factors other than the increased human capital for attendees. Two possibilities are either a signaling effect of attendance or positive selection of attendees not captured by the matching or fixed effects models. At the same time, because the attendee develops the thesis project with the employer, this development process could increase the worker's relevant human capital even before the thesis project is completed. Nonetheless, to be conservative, we view our results as upper bounds of the returns to increased human capital due to master's programs.

By four years after entry, the coefficient is around €2,800, and it is over €3,000 five to six years after program entry.[15] In percentage terms, attendees have around an eight-percent increase in earnings (from €36,800) five to six years after initial enrollment.[16] In contrast, the

[15] When we estimate a fixed effects model with a single post-schooling period, as in much previous work in the U.S., the coefficient is also around €3,000 (results available from the authors upon request).
[16] Estimation of the fixed effects models with log earnings as the dependent variable (dropping the small number of zero annual earnings) resulted also in 8% gain in earnings (see Table B4).

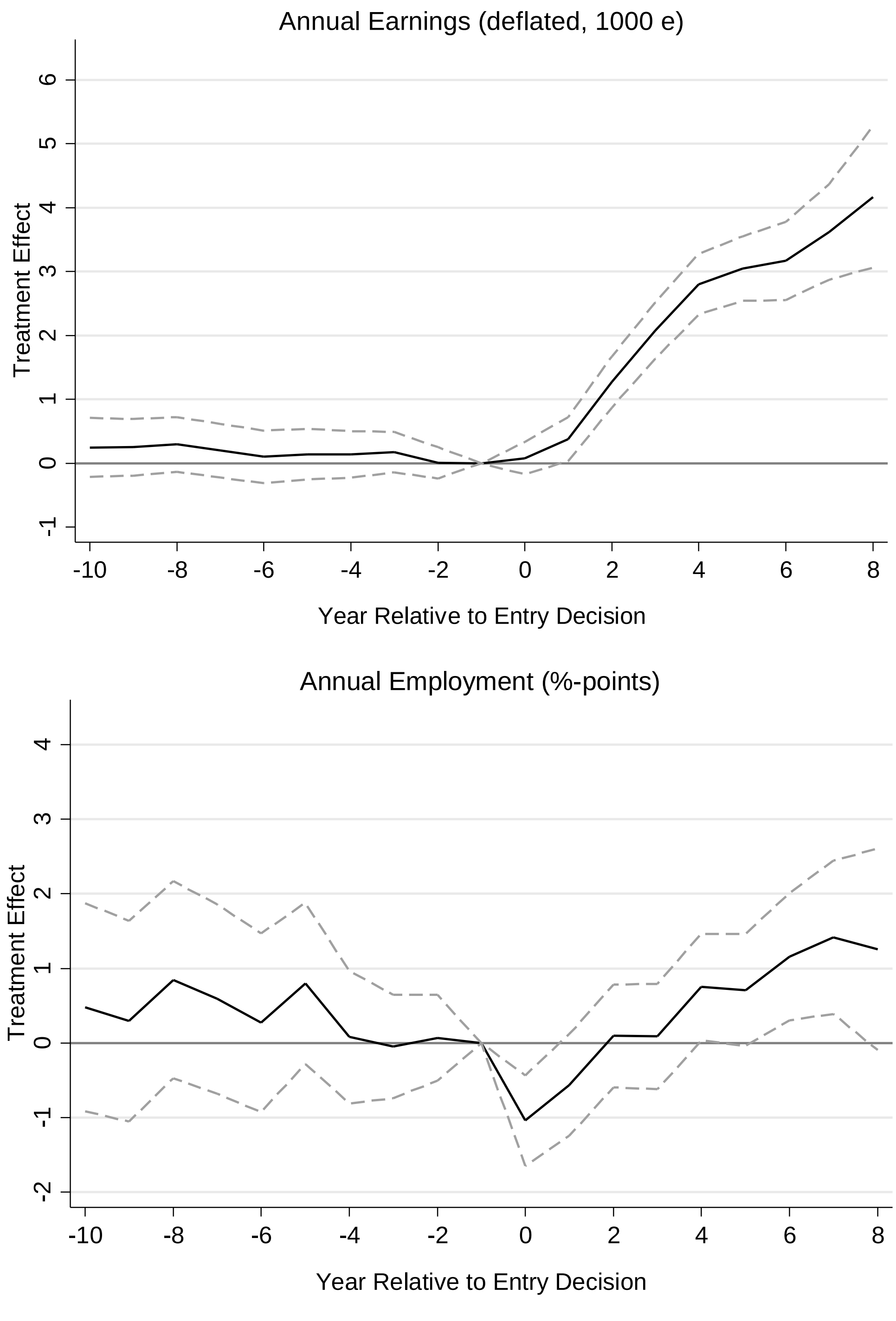
earnings differentials between attendees and the matched control group are small and not statistically different from zero in all the pre-enrollment time periods.

Table 2 – Fixed Effect Returns to Program Attendance (Matched Sample)

	Annual Earnings		Annual Employment	
Time Period	Coeff.	Std. Err.	Coeff.	Std. Err.
Attendees - Entry year	0.080	0.129	-0.01039***	0.00310
Attendees - 1 year after entry	0.380**	0.175	-0.00561	0.00347
Attendees - 2 years after entry	1.274***	0.205	0.00095	0.00351
Attendees - 3 years after entry	2.077***	0.225	0.00087	0.00361
Attendees - 4 years after entry	2.804***	0.242	0.00751**	0.00364
Attendees - 5 years after entry	3.047***	0.258	0.00710*	0.00383
Attendees - 6 years after entry	3.167***	0.311	0.01159***	0.00435
Attendees - 7 years after entry	3.624***	0.382	0.01418***	0.00524
Attendees - 8 years after entry	4.169***	0.563	0.01256*	0.00689
Attendees - 2 years before entry	0.007	0.125	0.00070	0.00294
Attendees - 3 years before entry	0.175	0.162	-0.00046	0.00353
Attendees - 4 years before entry	0.138	0.186	0.00080	0.00454
Attendees - 5 years before entry	0.144	0.201	0.00799	0.00551
Attendees - 6 years before entry	0.102	0.210	0.00273	0.00611
Attendees - 7 years before entry	0.198	0.215	0.00590	0.00648
Attendees - 8 years before entry	0.294	0.219	0.00849	0.00673
Attendees - 9 years before entry	0.251	0.226	0.00294	0.00687
Attendees - 10 years before entry	0.249	0.235	0.00478	0.00711
Number of observations	367,791		367,791	
Number of individuals	19,602		19,602	
Adjusted R-squared	0.686		0.344	

Notes: * = significant at 10%; ** = significant at 5%; *** = significant at 1% (all two-sided tests). The regressions also include controls for time relative to entry (not interacted with treatment status), dummy variables for calendar year, and age in years as listed in equation (2). Estimations are based on sample of attendants and matched non-attendants. Annual earnings are measured in 1,000 euro (deflated).

Figure 2 – Fixed Effects Results by Year Relative to Entry, Attendance Model
(with 95% Confidence Intervals)



Notes: The matched fixed effects regressions also include controls for time relative to entry (not interacted with attendance status), dummy variables for calendar year, and age in years as listed in equation (2). Reference year is t-1. Dashed lines indicate 95% confidence intervals.

To provide additional insight into the quantitative size of the total returns to education, we have calculated the discounted cumulated gains based on the estimates reported in Table 2. Following Koedel and Podgursky (2016), we use a 4% discount rate in the calculations. As reported in the Supplementary Online Appendix B, the total gains from this education without tuition fees are about €16,700 over the period 0–8 years after initial enrollment (Table B1). The rate of return per year attended is around €5,700 because the students, on average, attend polytechnic master’s programs for 2.94 years (mostly part time).

We also find a small increase in employment for master’s students relative to the matched control group. The difference is between 0.7 and 0.8 percentage points in years four and five. For periods six and seven the employment effects are larger. As before, the employment differences between the treated and control groups are insignificant in the pre-enrollment period, where program attendance could not have had a causal impact.

To assess the role of observables, we have estimated matched regression models with different sets of control variables. The results reported in Table B6 show that the estimates remain intact when we gradually exclude fixed effects as well as age and year dummies from the regression models after matching. We have also expanded the set of controls by adding 10 industry and 15 occupational groups to the matching procedure. The estimated effects of the program attendance are slightly lower after adding these controls (Table B7). The total earnings gains from the education are €14,100 over the period 0–8 (compared to €16,700 in the baseline). The estimated employment gains are close to zero.

Analyses based on Oster’s (2018) method show that the matched individual fixed effects results are robust to substantial selection on unobservables (Table 3). The method can be used to evaluate the value of δ, the ratio of selection on unobservables versus observables, for which the effect of interest is zero (see Columns 1 and 3).[17] Our results reveal that, for five and six years after enrollment, unobservables would need to be around 2.2–2.9 (3.5–4.6) times as important as observables in order to produce zero treatment effect of polytechnic master's program attendance on earnings (employment), i.e. $\beta_{1t} = 0$. Altonji *et al.* (2005) argue that the value of δ = 1 (i.e. equal selection on observables and unobservables) constitutes a reasonable cut-off for a robust result. Alternatively, the method can be used to estimate the bounds for estimated effect while assuming that δ = 1 (Columns 2 and 4). In all specifications, we can reject the hypothesis that the effect of attending vocational master's programs is zero. Unless selection on unobservables is more than twice as much as selection on observables (i.e. δ > 2), our results are robust to positive selection of students into vocational master's programs.

[17] Following Oster (2018) and Dahlen (2016), we assume that R_{max}, the unknown overall R-squared value of a hypothetical model, which controls for full set of observables and unobservables, is min{1, 1.3*(R^2 in the extended model}. R_{max} is not set to 1, because the earnings or employment cannot be fully explained even if the exhaustive set of controls would be included e.g. due to idiosyncratic variation in the outcome.

Table 3 – Fixed Effects Earnings and Employment Results (Matched Sample): Robustness to Omitted Variable Bias

	Annual Earnings		Annual Employment	
	(1)	(2)	(3)	(4)
Treatment Variable	$\tilde{\delta}$ for β=0 given R_{max}	Identified set given δ=1 and R_{max}	$\tilde{\delta}$ for β=0 given R_{max}	Identified set given δ=1 and R_{max}
Attendees - 4 years after entry	2.257	[2.804, 2.945]	5.491	[0.008, 0.012]
Attendees - 5 years after entry	2.238	[3.047, 3.177]	4.685	[0.007, 0.011]
Attendees - 6 years after entry	2.900	[3.167, 3.213]	3.497	[0.012, 0.013]
Attendees - 7 years after entry	3.613	[3.513, 3.624]	4.997	[0.014, 0.015]
R_{max}	0.916		0.496	

Notes: The Oster analysis is based on matched sample estimated with propensity score matching on two nearest neighbors as reported in Tables A1 and A3. Number of observations is 367,791 (Full sample). Results are computed using Oster's (2018) Stata package psacalc, and areg.

Baseline models include only (fully observed) controls for time dummy variables relative to entry (except for the year before) and these time dummies interacted with treatment status.

Extended models include the full set of controls as in Table 2: individual fixed effects, age and year fixed effects, time dummy variables relative to entry (except for the year before), and these time dummies interacted with treatment status.

We have also run placebo regressions where we have replaced our outcome variables of interest by pseudo outcomes that should not be affected by the treatment (Athey and Imbens, 2017). We use mother's total annual earnings and employment as pseudo outcomes, for which we should obtain estimates that are close to zero. Using longitudinal linkages in population census data, mother's earnings and employment are defined as in the baseline models for the offspring. We use mother's outcomes because the mother-children links are more complete than the father-children links and because mortality is higher among men at younger ages. We do not find significant effects on pseudo outcomes in the post-treatment periods (Table B8).

The primary advantage of the above models (based on equation 2) is that they make no assumptions about the endogeneity of completion. The primary disadvantage is that the returns to attendance that are measured combine the returns for dropouts with the returns for completers. Next, we turn to the completion model as estimated in equation (3), under the nontrivial assumption that the differences between completers and dropouts are time-invariant and therefore captured in the fixed effects model.

Table 4 contains the regression results from the specification for completion where we simply add a dummy variable for completion to the attendance model.[18] In this model – shown in equation (3) – the effect of completion is constrained to be constant across time. As in Table 2, the table contains the results for annual earnings (first two columns) and annual employment (second two columns).

[18] See Supplementary Table C1 for descriptive statistics for the samples of completers and dropouts.

Table 4 – Fixed Effect Returns to Master's Degree, Specification 1 (Matched Sample)

	Annual Earnings		Annual Employment	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Master's Degree	1.655***	0.320	0.00150	0.00411
Attendees - Entry year	0.080	0.129	-0.01039***	0.00310
Attendees - 1 year after entry	0.380**	0.175	-0.00561	0.00347
Attendees - 2 years after entry	1.110***	0.209	0.00080	0.00354
Attendees - 3 years after entry	1.468***	0.261	0.00032	0.00395
Attendees - 4 years after entry	1.880***	0.311	0.00667	0.00437
Attendees - 5 years after entry	1.971***	0.346	0.00613	0.00481
Attendees - 6 years after entry	2.032***	0.402	0.01056**	0.00532
Attendees - 7 years after entry	2.475***	0.468	0.01314**	0.00612
Attendees - 8 years after entry	3.000***	0.651	0.01150	0.00755
Attendees - 2 years before entry	0.006	0.125	0.00070	0.00294
Attendees - 3 years before entry	0.174	0.162	-0.00046	0.00353
Attendees - 4 years before entry	0.138	0.186	0.00080	0.00454
Attendees - 5 years before entry	0.143	0.201	0.00799	0.00551
Attendees - 6 years before entry	0.102	0.210	0.00273	0.00611
Attendees - 7 years before entry	0.198	0.215	0.00590	0.00648
Attendees - 8 years before entry	0.294	0.219	0.00849	0.00673
Attendees - 9 years before entry	0.250	0.226	0.00294	0.00687
Attendees - 10 years before entry	0.250	0.235	0.00478	0.00711
Number of observations	367,791		367,791	
Number of individuals	19,602		19,602	
Adjusted R-squared	0.686		0.344	

Notes: * = significant at 10%; ** = significant at 5%; *** = significant at 1% (all two-sided tests). The regressions also include controls for time relative to entry (not interacted with treatment status), dummy variables for calendar year, and age in years as listed in equation (3). Estimations are based on sample of attendants and matched non-attendants. Annual earnings are measured in 1,000 euro (deflated).

In this model, the completion of a master's degree is associated with an increase in annual earnings of around €1,700, or approximately 4.5 percent of average earnings in the comparison time period one year before enrollment. In contrast, the completion of a degree has an insignificant effect on employment that is almost zero. The model includes two sets of dummy variables for years relative to initial enrollment, one set for the entire sample and another set interacted with a dummy variable for the treatment group (i.e. students). Consequently, the dummy variable for completing a master's program captures the additional gain (or loss) in earnings / employment for graduates holding constant the returns to attendance (as measured by these dummy variables).

Our second specification of the returns to degree completion allows for time-varying effects of degree completion. Instead of including a dummy variable for degree completion, we estimate separate regressions for completers and dropouts. The results from this model are shown in Table 5. For simplicity, the table only contains the results for time periods after initial enrollment. However, Figure 3 shows the estimated effects before entry year. The dummy variables for time to initial enrollment capture the change in earnings relative to the matched control group of individuals who did not attend master's programs. As in previous results, the reference time period for these dummy variables is one year before enrollment.

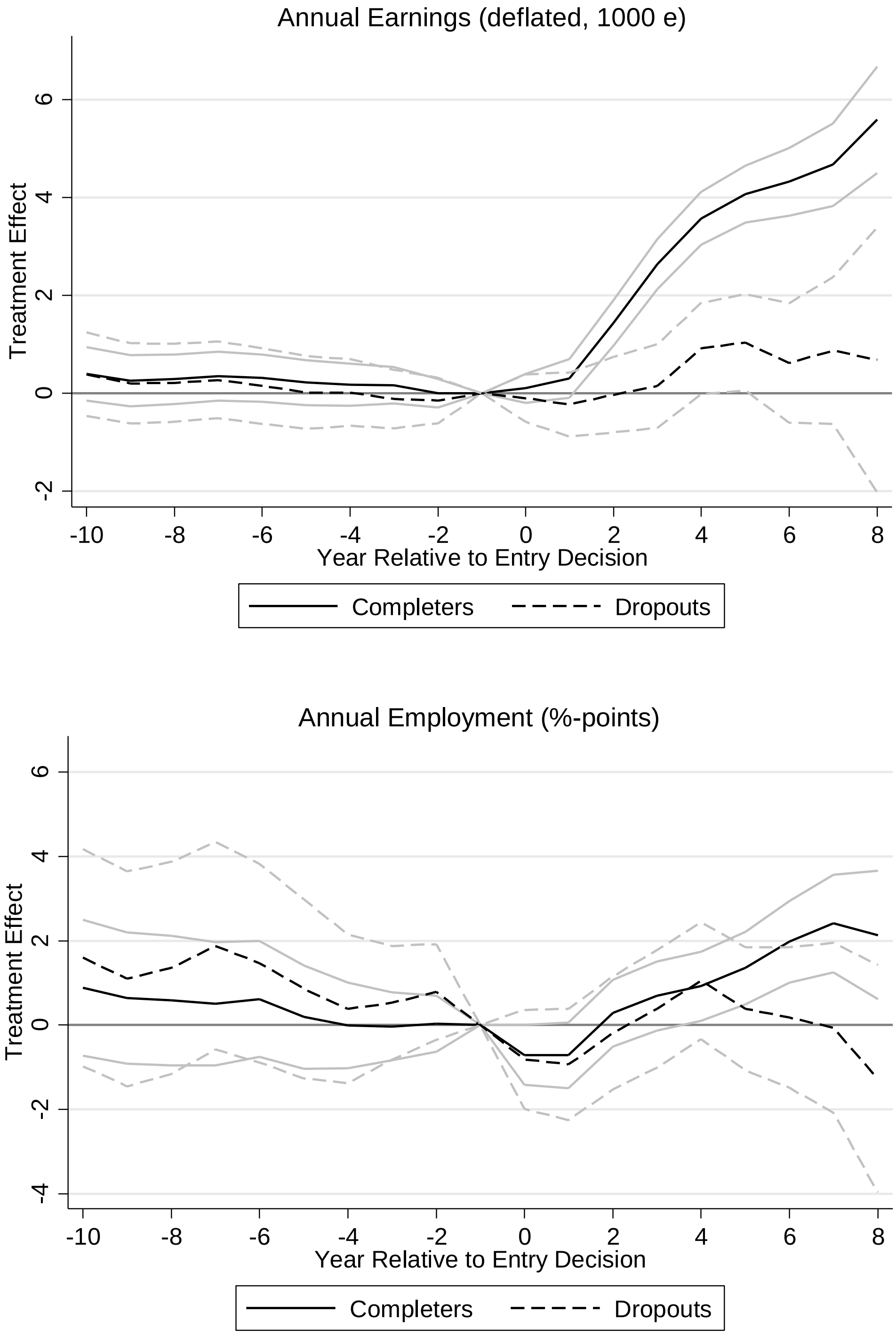
For earnings, completers have noticeably higher earnings than the control group. By three years after enrollment, the coefficient is over €2,600, or seven percent of average earnings in the year before enrollment. By five years after enrollment, the coefficient is around €4,100, or 11 percent of average earnings the year before enrollment. The earnings benefits for dropouts are much smaller, with coefficients around €1,000 four to five years after enrollment. Note, however, that degree completion is probably endogenous, and thus our estimates of gain to degree completion likely represent an upper bound because of positive selection.

Table 5 – Fixed Effect Returns to Master's Degree, Specification 2 (Matched Sample)

	Annual Earnings		Annual Employment	
Time Period	Completers	Dropouts	Completers	Dropouts
Entry year	0.098	-0.102	-0.00707**	-0.00815
	(0.151)	(0.248)	(0.00360)	(0.00601)
1 year after entry	0.303	-0.233	-0.00720*	-0.00934
	(0.204)	(0.334)	(0.00395)	(0.00673)
2 years after entry	1.442***	-0.032	0.00283	-0.00189
	(0.237)	(0.393)	(0.00404)	(0.00685)
3 years after entry	2.646***	0.145	0.00692*	0.00386
	(0.261)	(0.435)	(0.00418)	(0.00712)
4 years after entry	3.578***	0.916*	0.00922**	0.01055
	(0.276)	(0.475)	(0.00417)	(0.00708)
5 years after entry	4.073***	1.038**	0.01354***	0.00385
	(0.297)	(0.503)	(0.00438)	(0.00744)
6 years after entry	4.325***	0.616	0.01976***	0.00180
	(0.353)	(0.624)	(0.00493)	(0.00852)
7 years after entry	4.676***	0.870	0.02414***	-0.00065
	(0.431)	(0.766)	(0.00592)	(0.01028)
8 years after entry	5.593***	0.681	0.02138***	-0.01270
	(0.556)	(1.379)	(0.00779)	(0.01378)
Number of observations	262,007	108,013	262,007	108,013
Number of individuals	14,252	6,063	14,252	6,063
Adjusted R-squared	0.694	0.673	0.338	0.363

Notes: * = significant at 10%; ** = significant at 5%; *** = significant at 1% (all two-sided tests). Standard errors are in parentheses. Each column contains the results from a separate regression. The regressions also include controls for time relative to entry (not interacted with treatment status), dummy variables for calendar year, and age in years as listed in equation (2). The estimated coefficients for the periods prior to entry are not reported. Estimations are based on sample of attendants and matched non-attendants. Annual earnings are measured in 1,000 euro (deflated).

Figure 3 – Fixed Effects Results by Completion Status
(with 95% Confidence Intervals)



Notes: The matched fixed effects regressions also include controls for time relative to entry (not interacted with attendance status), dummy variables for calendar year, and age in years as listed in equation (2). Reference year is t-1. Lines in gray color indicate 95% confidence intervals.

For employment, completers have higher employment levels, with coefficients of around one percentage point in years four and five. However, we cannot distinguish whether employment outcomes are better for completers than for dropouts because the coefficients for dropouts are estimated so imprecisely that the confidence intervals for dropouts and completers overlap.

In summary, attendance in a vocational master's program is associated with increases in annual earnings in the post-enrollment period. When we model the returns to completion, under the assumption that completion is exogenous once we control for time, age, and individual fixed effects, then the increases in earnings are larger for completers than for dropouts. This pattern of results is similar for employment, except that the estimates for dropouts are too imprecisely estimated to make definite inferences about their post-enrollment employment.

5.4 Results for Specific Subgroups

Next, we investigate whether the returns to vocational master's programs differ across key demographic characteristics, field of study, or job mobility. For simplicity, we present only the results from the attendance model where the dependent variable is annual earnings, and we estimate separate regressions for each subgroup. Table 6 contains the coefficients and standard errors for the post-enrollment returns for attendees (versus the relevant matched comparison group) by age, gender, region, and year of entry. As always, the reference time period is the year before entry.

Table 6 – Fixed Effect Earnings Returns to Program Attendance by Demographic Group (Matched Sample)

	Age at Entry		Gender		Region		Entry Year	
Time Period	25 to 34	35 to 55	Females	Males	Helsinki	Other areas	2002–2005	2006–2009
Attendees - Entry year	0.249	-0.128	-0.029	0.135	-0.070	0.024	-0.209	0.138
	(0.183)	(0.186)	(0.165)	(0.198)	(0.251)	(0.148)	(0.278)	(0.144)
Attendees - 1 year after entry	0.933***	-0.491**	0.489**	0.254	0.356	0.321	0.363	0.248
	(0.255)	(0.239)	(0.225)	(0.275)	(0.357)	(0.198)	(0.411)	(0.193)
Attendees - 2 years after entry	1.268***	0.763***	1.505***	1.011***	1.746***	0.969***	1.256**	1.211***
	(0.304)	(0.269)	(0.253)	(0.340)	(0.420)	(0.229)	(0.489)	(0.225)
Attendees - 3 years after entry	1.493***	1.727***	2.138***	1.679***	2.755***	1.502***	1.973***	2.091***
	(0.335)	(0.295)	(0.279)	(0.374)	(0.470)	(0.252)	(0.573)	(0.247)
Attendees - 4 years after entry	2.493***	2.426***	2.910***	3.125***	3.274***	2.262***	2.082***	2.804***
	(0.357)	(0.323)	(0.292)	(0.410)	(0.516)	(0.270)	(0.608)	(0.263)
Attendees - 5 years after entry	2.913***	2.649***	3.196***	3.502***	3.718***	2.825***	2.927***	3.077***
	(0.386)	(0.349)	(0.312)	(0.447)	(0.545)	(0.286)	(0.663)	(0.281)
Attendees - 6 years after entry	2.584***	2.716***	3.380***	3.615***	3.278***	3.094***	3.650***	3.147***
	(0.467)	(0.415)	(0.359)	(0.563)	(0.685)	(0.333)	(0.694)	(0.343)
Attendees - 7 years after entry	3.167***	3.429***	3.752***	3.737***	3.756***	3.567***	3.920***	3.712***
	(0.565)	(0.513)	(0.437)	(0.711)	(0.813)	(0.413)	(0.736)	(0.448)
Attendees - 8 years after entry	3.277***	3.090***	4.364***	4.459***	4.355***	3.816***	4.154***	4.211***
	(0.922)	(0.667)	(0.549)	(1.190)	(1.352)	(0.522)	(0.769)	(0.847)
Number of observations	180,760	186,667	231,454	136,028	107,804	260,339	58,423	309,497
Number of individuals	9,991	9,947	12,473	7,380	5,902	13,999	3,045	16,983
Adjusted R-squared	0.665	0.685	0.624	0.725	0.669	0.694	0.694	0.683

Notes: * = significant at 10%; ** = significant at 5%; *** = significant at 1% (all two-sided tests). Standard errors are in parentheses. Each column contains the results from a separate regression. The regressions also include controls for time relative to entry (not interacted with treatment status), dummy variables for calendar year, and age in years as listed in equation (2). Dependent variable is annual earnings in 1,000 euro (deflated).

The table shows modest differences in returns by demographic group. For age, the two cohorts have similar returns starting in year 2. For example, five years after, the returns for the younger cohort are around €2,900, compared to under €2,700 for the older cohort. In percentage terms, these earnings gains are 8.6 percent for the younger cohort and 6.7 percent for the older cohort. However, this difference in year 5 and all differences starting in year 2 are not statistically different.

For gender, females have slightly lower gains compared to males starting in year four, but the difference is usually insignificant. In year five, the returns are €3,200 for women and €3,500 for men. Because women in our sample have lower earnings than men, the percentage increase is higher for women: 10.0 percent versus 7.8 percent.

The increase in earnings is higher (but not statistically significant in most cases) in the Helsinki metropolitan region compared with other regions in Finland. Five years after entry, the gains are €3,700 (or 9.3 percent) for Helsinki and €2,800 (or 8.0 percent) elsewhere in the country.

With respect to entry year, the earlier and later cohorts have similar earnings gains. For instance, students entering master's programs between 2002 and 2005 have higher earnings of €2,900 five years after entry, compared with €3,100 for students entering master's programs between 2006 and 2009. In both cohorts, the gain is approximately eight percent of average earnings the year before entry. The first trial years involved only small number of students, making it difficult to draw precise earnings projections. Another concern with the estimates for the early years is that, with a new program, employers and attendees may only gradually learn about the labor-market value of degrees.

Table 7 – Fixed Effect Earnings Returns to Program Attendance by Field of Education (Matched Sample)

Time Period	Health	Business	Tech & Trades
Attendees - Entry year	0.027	0.064	0.005
	(0.191)	(0.274)	(0.255)
Attendees - 1 year after entry	-0.056	0.695*	-0.059
	(0.262)	(0.376)	(0.330)
Attendees - 2 years after entry	0.854***	1.558***	0.816**
	(0.291)	(0.438)	(0.397)
Attendees - 3 years after entry	1.818***	2.387***	1.070**
	(0.316)	(0.490)	(0.445)
Attendees - 4 years after entry	2.781***	2.452***	2.783***
	(0.334)	(0.524)	(0.496)
Attendees - 5 years after entry	3.129***	2.330***	3.540***
	(0.349)	(0.563)	(0.526)
Attendees - 6 years after entry	3.663***	1.935***	2.887***
	(0.403)	(0.657)	(0.653)
Attendees - 7 years after entry	4.515***	2.503***	3.473***
	(0.492)	(0.781)	(0.788)
Attendees - 8 years after entry	5.374***	2.681**	2.548**
	(0.604)	(1.046)	(1.015)
Number of observations	127,019	101,666	94,162
Number of individuals	6,843	5,517	5,153
Adjusted R-squared	0.617	0.677	0.725

Notes: * = significant at 10%; ** = significant at 5%; *** = significant at 1% (all two-sided tests). Standard errors are in parentheses. Each column contains the results from a separate regression. The regressions also include controls for time relative to entry (not interacted with treatment status), dummy variables for calendar year, and age in years as listed in equation (2). Dependent variable is annual earnings in 1,000 euro (deflated).

Next, we separate returns by field of study (Table 7).[19] The three main fields of study in the polytechnics are: (1) health care and welfare, (2) business and administration, and (3) technology and trades. Table 7 contains the returns to attendance, where the sample is split into these three fields of study. Short-run gains from the program are noticeably high for business students, but from year six onwards, the highest gains are for health, although the differences by field of study are often statistically insignificant. By five to six years after entry, the earnings gains are around €3,100–€3,600 for health, €2,900–€3,500 for technology and trades, and €1,900–€2,300 for business. In percentages, the earnings increase is also

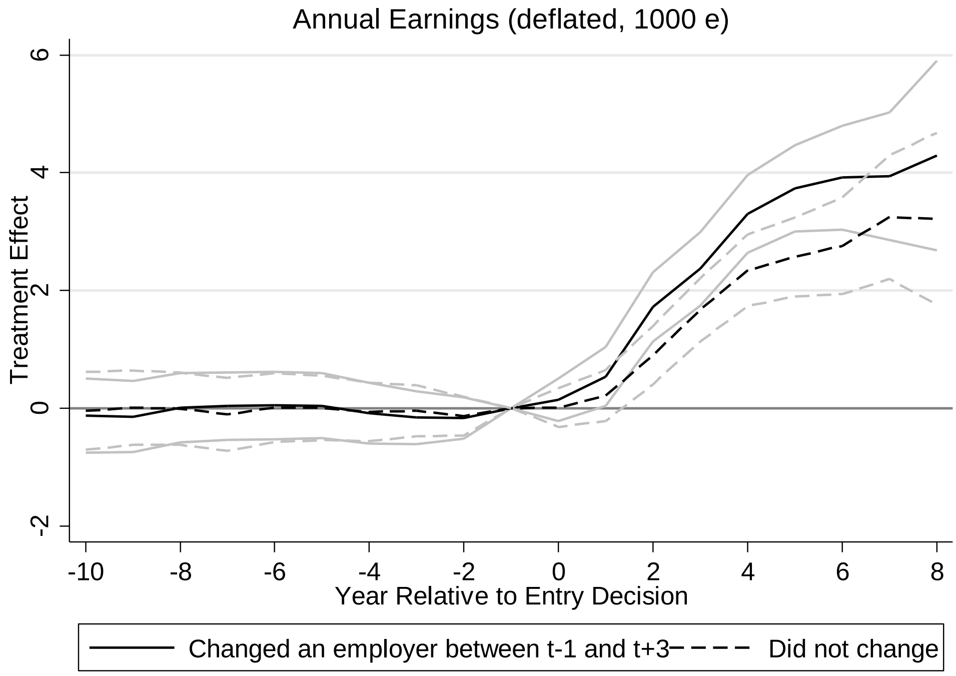
[19] Master's degree is usually completed in the same field as the bachelor's degree. The completion of a master's degree in health care does not imply that the graduate can work as a certified nurse (Ministry of Education and Culture, 2012).

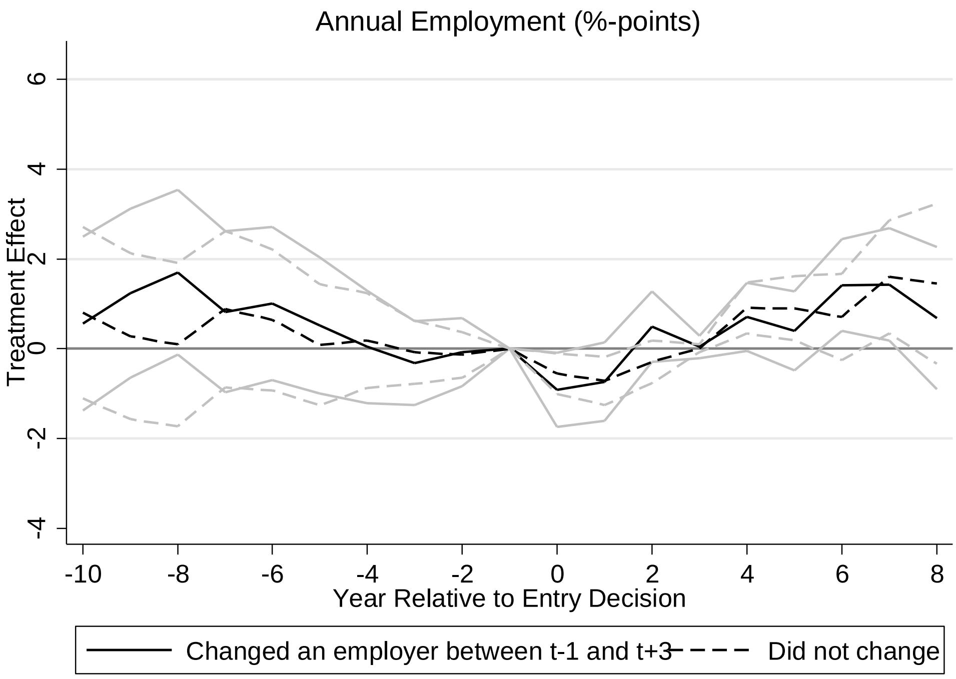
highest in health (10.4–12.2 percent) because on average their prior earnings are the lowest (€30,000), followed by business (€37,700) and technology and trades (€45,700).

Because nearly all persons work throughout the sample period, we can also study whether the results are robust to changing employer or not. For this purpose, we utilize information on the employer a year prior to entry (at t-1) and three years after the entry (t+3). The employer code can be matched for 93 percent of the attendants, of whom around half (51%) change their employer between the two measurement points. To estimate the heterogeneity of the returns to education, we separate the sample by job change status under the strong assumption that the decision to change jobs is exogenous.

Figure 4 illustrates the estimates reported in the Supplementary Online Appendix B (Table B2). The pattern of coefficients – steep growth until the year 4 or 5 followed by slower growth – is similar for the two groups, but the coefficients are larger for the sample that switches jobs. However, we cannot reject the hypothesis that the earnings gains are the same between those who switch jobs and those who do not. Job switchers may receive a larger increase in earnings from switching jobs, consistent with the standard theory of employee turnover and earnings (Ehrenberg and Smith, 2009). However, Figure 4 suggests that attendees receive higher earnings regardless of whether they switch employers. Thus, the similarity of results between switchers and stayers does not suggest that people are not returning to school after receiving a promotion (in order to learn needed skills in their new position), nor does it suggest that people return to school simply to obtain a promotion from their new employer.

Figure 4 – Fixed Effects Results by Employer Change, Attendance Model (with 95% Confidence Intervals)





Notes: The matched fixed effects regressions also include controls for time relative to entry (not interacted with attendance status), dummy variables for calendar year, and age in years as listed in equation (3). Reference year is t-1. Estimates are conditional on being employed in t-1 and t+3. The comparison group has same employer change status as the treated. Lines in gray color indicate 95% confidence intervals.

Our final analysis looks at whether vocational master's programs relocate their students to better job titles. Although direct information on promotions is not available, data on occupation allow us to rank occupations into three job titles: managers, professionals, and other occupational categories.[20] We calculate the percentage of individuals in each job title at different points in time relative to enrollment, separately for master's entrants and the matched sample of non-entrants.

In our supplementary analysis (Table B3) three empirical patterns stand out. First, upward mobility in occupational hierarchy is more likely among the entrants than matched non-entrants during the six-year follow-up period. Second, downward mobility is similar in both groups. Third, entrants seem to move to better positions (relative to non-entrants) gradually over time, arguably, as opportunities for professional (and managerial) tasks emerge. Because upward mobility is greater than downward mobility among the entrants and matched non-entrants, this analysis suggests that polytechnic education has not led to an increase in the proportion of workers with high vocational education in "non-professional" tasks (cf. Gottschalk and Hansen, 2003). A comprehensive analysis of the occupational changes is necessary to draw stronger (and more causal) inferences about changes in occupational hierarchy.

6. Discussion

This paper estimates the labor-market returns to vocational master's programs, a new and growing sector of higher vocational education. We use matching methods on complete population data to identify a sample of individuals who did not attend these programs but have similar demographic characteristics and labor-market histories, and we run an individual fixed effects model to capture any time-invariant differences across individuals.

[20] These occupational levels are based on standard ISCO classifications. Of the polytechnic master's students, 7.2% are managers, 33.4% are professionals, and 59.4% belong to other occupational categories.

Attendance in vocational master's programs is associated with higher earnings of eight percent or more five to six years after entry. Under the assumption that completion is exogenous after controlling for individual and time fixed effects, we find particularly sizable earnings returns to the completion of a vocational master's degree. We find few statistically significant differences in returns across demographic groups and fields of study, even though the most pronounced of these differences are higher returns for health.

Despite the combination of matching estimators and fixed effects regression, potential concerns may persist about the nonrandom decision of individuals to attend vocational master's programs. However, unless selection on unobservables is more than two times larger than selection on observables (based on the methods in Oster, 2018), our results demonstrate a positive return to attending a vocational master's program. By looking in more detail at people who switch jobs versus those who do not, we also cast doubt on the hypothesis that workers attend vocational master's programs because they just received a promotion or in order to receive a promotion.

We are not aware of any prior work on the returns to these degrees. Although our results are from one country (Finland), other countries such as Austria, Germany, and Switzerland offer similar programs. Because individuals with vocational bachelor's degrees rarely access academic master's programs, these vocational master's degrees are the best opportunity for such individuals to obtain formal post-graduate education. Based on Finland's experience, vocational master's programs substantially improve earnings. However, these master's programs have not been designed for unemployed: more than 95 percent of entrants have been working before and after the entry to the program. Finally, although we show that workers clearly benefit from these programs in terms of discounted future earnings, research should also focus on obtaining measures of the cost to government of these educational programs in order to compare the benefits of vocational master's programs to their costs. This would inform policy makers about how to split funding and other resources between universities and vocational tertiary education providers in order to best support work-related skills.

References

Abadie, Alberto, and Guido W. Imbens. 2016. Matching on the Estimated Propensity Score. *Econometrica*, 84(2): 781–807.

Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber. 2005. Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools. *Journal of Political Economy*, 113: 151–184.

Athey, Susan, and Guido W. Imbens. 2017. The State of Applied Econometrics: Causality and Policy Evaluation. *Journal of Economic Perspectives*, 31(2): 3–32.

Austin, Peter C. 2009. Balance Diagnostics for Comparing the Distribution of Baseline Covariates Between Treatment Groups in Propensity Score Matched Samples. *Statistics in Medicine*, 28(25): 3083–3107.

Belfield, Clive, and Thomas Bailey. 2017. The Labor-Market Returns to Sub-Baccalaureate College: A Review. Center for Analysis of Postsecondary Education and Employment Working Paper.

Blundell, Richard, Lorraine Dearden, and Barbara Sianesi. 2005. Evaluating the Effect of Education on Earnings: Models, Methods and Results from the National Child Development Survey. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 168(3), 473–512.

Böckerman, Petri, Mika Haapanen, and Christopher Jepsen. 2018. More Skilled, Better Paid: Labour-Market Returns to Postsecondary Vocational Education. *Oxford Economic Papers*, 70(2), 485–508.

Böckerman, Petri, Ulla Hämäläinen, and Roope Uusitalo. 2009. Labor Market Effects of the Polytechnic Education Reform: The Finnish Experience, *Economics of Education Review*, 28(6): 672–681.

Brunello, Giorgio, and Lorenzo Rocco. 2015. The Effects of Vocational Education on Adult Skills and Wages. OECD Social, Employment and Migration Working Papers. Organisation for Economic Co-operation and Development, Paris.

Cellini, Stephanie, and Latika Chaudhary. 2014. The Labor Market Returns to a For-Profit College Education. *Economics of Education Review*, 43(1): 125–140.

Cellini, Stephanie, and Nicholas Turner. 2016. Gainfully Employed? Assessing the Employment and Earnings of For-Profit College Students Using Administrative Data. NBER Working Paper No. 22287. May 2016.

Dahlen, Heather M. 2016. The Impact of Maternal Depression on Child Academic and Socioemotional Outcomes. *Economics of Education Review*, 52: 77–90.

Dearden, Lorraine, Steven McIntosh, Michal Myck, and Anna Vignoles. 2002. The Returns to Academic and Vocational Qualifications in Britain. *Bulletin of Economic Research*, 54: 249–274.

Gottschalk, Peter, and Michael Hansen. 2003. Is the Proportion of College Workers in Noncollege Jobs Increasing? *Journal of Labor Economics*, 21(2): 449–171.

Hällsten, Martin. 2012. Is It Ever Too Late to Study? The Economic Returns to Late Tertiary Degrees in Sweden, *Economics of Education Review*, 31(1): 179–194.

Heinrich, Carolyn J., Peter R. Mueser, Kenneth R. Troske, Kyung-Seong Jeon, and Daver C. Kahvecioglu. 2013. Do Public Employment and Training Programs Work? *IZA Journal of Labor Economics*, 2(6).

Horrigan, John B. 2016. Lifelong Learning and Technology. Pew Research Center.

Iacus, Stefano M., Gary King, and Giuseppe Porro. 2012. Causal Inference without Balance Checking: Coarsened Exact Matching. *Political Analysis*, 20(1): 1–24.

ILO. 2011. A Skilled Workforce for Strong, Sustainable and Balanced Growth: A G20 Training Strategy (Report). International Labour Office, Geneve.

Jacobson, Louis S., Robert J. LaLonde, and Daniel G. Sullivan. 2005a. Estimating the Returns to Community College Schooling for Displaced Workers. *Journal of Econometrics*, 125(1–2): 271–304.

Jacobson, Louis S., Robert J. LaLonde, and Daniel G. Sullivan. 2005b. The Impact of Community College Retraining on Older Displaced Workers: Should We Teach Old Dogs New Tricks? *Industrial and Labor Relations Review*, 58(3): 398–415.

Jepsen, Christopher, Kenneth Troske, and Paul Coomes. 2014. Labor-Market Returns to Community College Degrees, Diplomas, and Certificates, *Journal of Labor Economics*, 32(1): 95–121.

Jepsen, Christopher, Peter Mueser, and Kyung-Seong Jeon. 2016. The Benefits of Alternatives to Conventional College: Labor-Market Returns to Proprietary Schooling, IZA Discussion Paper 10007.

Koedel, Cory, and Michael Podgursky. 2016. Chapter 6 - Teacher Pensions. In Eric A. Hanushek, Stephen Machin, and Ludger Woessmann (Eds). *Handbook of the Economics of Education*, Vol. 5, pp. 281–303. Elsevier: Amsterdam.

Ministry of Education and Culture. 2012. Selvitys ylempien ammattikorkeakoulututkintojen asemasta työelämässä ja uudistuksen vaikutuksesta koulutusjärjestelmään ja työelämään (in Finnish), Helsinki.

Mueser, Peter R., Troske, Kenneth R., and Goriaslavsky, Alexey. 2007. Using State Administrative Data to Measure Program Performance, *Review of Economics and Statistics*, 89(4): 761–783.

OECD. 2014. Skills Beyond School: Synthesis Report, OECD Reviews of Vocational Education and Training, OECD Publishing. DOI: http://dx.doi.org/10.1787/9789264214682-en

OECD. 2017. Getting Skills Right: Skills for Jobs Indicators, OECD Publishing, Paris.

Oster, Ester. 2018. Unobservable Selection and Coefficient Stability: Theory and Evidence. *Journal of Business & Economic Statistics*, forthcoming. DOI: http://dx.doi.org/10.1080/07350015.2016.1227711

Pratt, John, Yvonne Hillier, and John Mace. 1999. Markets and Motivation in Part Time Postgraduate Education, *Studies in Higher Education*, 24(1): 95–107.

Pratt, John, Tauno Kekäle, Peter Maassen, Inkeri Papp, Juan Perellon, and Minna Uitti. 2004. Equal, but Different: An Evaluation of the Postgraduate Polytechnic Experiment in Finland. Tampere: Finnish Higher Education Evaluation Council.

Stenberg, Anders, and Olle Westerlund. 2016. Flexibility at a Cost – Should Governments Stimulate Tertiary Education for Adults? *The Journal of the Economics of Ageing*, 7: 69–86.

Supplementary Online Appendix

A) Matching Results (incl. Tables and Figures)

Table A1 shows the results of the probit model that we use to estimate the propensity scores and the two nearest neighbors as described in Section 4.1 of the main text. Table A2 shows the covariate balance for the unmatched sample and Table A3 shows the balance for the matched sample. Figure A1 confirms that we have sufficient common support for each entry year given the large size of the control population.

Figure A2 contains the propensity score matching estimator results for mean annual earnings (top panel) and employment (bottom panel), along with the associated 95 percent confidence interval (two-sided test). On the horizontal or *x*-axis is the number of years since initial enrollment, from ten years before enrollment (-10) to eight years after initial enrollment (8). Each estimator is the average treatment effect on the treated, i.e. the increase in earnings or employment associated with attending vocational master’s programs.

Vocational master’s students have significantly higher earnings than the matched sample of non-students starting two years after the enrollment decision. To address the potential endogeneity concern of using year 0 earnings as a matching variable, we have also re-done the matching analysis excluding year 0 earnings as additional control variables. We never include year 0 employment as a control variable because it is measured at the end of the year, i.e. after enrollment.

A comparison of two results shows that the inclusion of year 0 earnings as additional controls reduces the treatment effect in year 0. In subsequent years, the matching estimate with year 0 earnings controls is slightly lower than the matching estimate without year 0 earnings controls. Four to six years after the enrollment decision, vocational master’s students have higher earnings of approximately €3,000 in our preferred model including year 0 earnings as control variables. Because the data are for students who enter between 2002 and 2009, and our most recent year of data is 2014, the estimates for years 6 and beyond are based on the subset of students who entered in early years. Thus, we mostly focus on the estimates for year 5 and earlier.

The results for employment are less pronounced, as expected given the high employment levels in excess of 95 percent for vocational master’s students, even in the pre-enrollment periods. In most periods, employment is not significantly different between the treatment group and the matched control group. The small dip in employment at year 0 is likely a factor of including year 0 earnings but not employment as control variables, as there is no dip in employment when we exclude year 0 earnings as control variables (Figure A3).

Results from Coarsened Exact Matching (CEM) are similar to the propensity score matching results (see Figure A4).

Table A1 – Probit Results for Entry to Polytechnic Master's Program

Variable	(1) Coeff.	(2) Std. Err.
Earnings, t - 10	0.0195**	0.0085
Earnings, t - 9	0.0177*	0.0092
Earnings, t - 8	0.0064	0.0088
Earnings, t - 7	-0.0233***	0.0089
Earnings, t - 6	-0.0081	0.0088
Earnings, t - 5	-0.0053	0.0083
Earnings, t - 4	0.0016	0.0081
Earnings, t - 3	0.0279***	0.0078
Earnings, t - 2	0.1072***	0.0175
Earnings squared, t - 2	-0.0117***	0.0024
Earnings, t - 1	0.0657***	0.0179
Earnings squared, t - 1	-0.0031	0.0023
Earnings, t	0.0119***	0.0014
Earnings squared, t	-0.0001***	0.0000
Employed, t - 10	-0.0120	0.0138
Employed, t - 9	0.0308**	0.0138
Employed, t - 8	0.0266*	0.0139
Employed, t - 7	-0.0042	0.0144
Employed, t - 6	-0.0086	0.0150
Employed, t - 5	0.0050	0.0165
Employed, t - 4	0.0947***	0.0198
Employed, t - 3	0.1809***	0.0251
Employed, t - 2	0.1099***	0.0301
Employed, t - 1	0.1090***	0.0332
Age at entry	0.1097***	0.0092
Age at entry squared	-0.0012***	0.0001
Female	0.2692***	0.0594
Female × Age at entry	0.0000	0.0000
Swedish language	-0.0054***	0.0016
Other languages	-0.0724**	0.0339
Not living in the region of birth	0.1830***	0.0508
Enrolled in any education, t - 1	0.1097***	0.0092
Enrolled in any education, t - 2	-0.0012***	0.0001
Enrolled in university education, t - 1	0.2692***	0.0594
Enrolled in university education, t - 2	-0.0054***	0.0016
BA-degree from tech & trades (ref. = business)	-0.0724**	0.0339
BA-degree from health care	0.1830***	0.0508
BA-degree from other fields	0.0211**	0.0101
Years from BA-degree to entry	0.2427***	0.0271
Years from BA-degree to entry squared	-0.0140***	0.0008
No. of degree-leading education programs attended in 7 years (ref. = 0)		
- One program	0.0877***	0.0180
- Two or more	-0.0226	0.0290
Study loan (€1,000)	-0.0076***	0.0021
Comprehensive school grade (4-10)	0.0601***	0.0094

Table A1 (Continued)

Variable	(1) Coeff.	(2) Std. Err.
Ever completed high school	-0.0960**	0.0474
Native language score is 1	0.0182	0.0537
Native language score is 2	0.0572	0.0504
Native language score is 3	0.0430	0.0498
Native language score is 4	0.0868*	0.0506
Native language score is 5	0.0717	0.0527
English language score is 1	0.0582	0.0479
English language score is 2	0.0671	0.0475
English language score is 3	0.0691	0.0478
English language score is 4	0.0484	0.0486
English language score is 5	0.0582	0.0502
Mathematics score is 1	0.0447**	0.0191
Mathematics score is 2	0.0202	0.0176
Mathematics score is 3	0.0059	0.0176
Mathematics score is 4	-0.0131	0.0195
Mathematics score is 5	0.0020	0.0233
Married or cohabiting	0.0923***	0.0298
Married or cohabiting × Female	-0.0476	0.0379
Has kids under 7	-0.0947***	0.0182
Has kids under 7 × Female	0.1303***	0.0239
Spouse employed	0.0172	0.0258
Spouse employed × Female	-0.0227	0.0327
Spouse’s income	-0.0141*	0.0078
Spouse’s income × Female	0.0131*	0.0079
Mother's education Lower tertiary	0.0218	0.0235
Mother's education Master's	0.0466*	0.0274
Mother's education Doctorate	0.0713	0.0599
Mother's education Basic/Unknown	0.0148	0.0179
Mother's education High school	0.0415	0.0464
Mother's education Vocational school	0.0196	0.0180
Father's education Lower tertiary	0.0050	0.0263
Father's education Master's	0.0147	0.0335
Father's education Doctorate	-0.0291	0.1147
Father's education Basic/Unknown	-0.0124	0.0163
Father's education High school	-0.0157	0.0373
Father's education Vocational school	0.0026	0.0155
Mother entrepreneur, not farmer (in '85 or '95)	-0.0011	0.0146
Mother employee in prof. occ. (in '85 or '95)	-0.0128	0.0119
Father entrepreneur, not farmer (in '85 or '95)	-0.0169	0.0136
Father employee in prof. occ. (in '85 or '95)	-0.0272	0.0173
Municipal level unemployment rate (NUTS-5)	-0.5110*	0.2800
Number of observations	773,553	
Log-likelihood	-36,740	
Pseudo R-squared	0.0950	

Notes: Standard errors clustered at the individual level are in parentheses. Statistical significance in two-sided tests are denoted by * for the ten-percent level, ** for the five-percent level, and *** for the one-percent level. All models also include dummies for missing earnings and zero earnings, missing comprehensive school grade, and region of residence prior to entry (NUTS-3) fixed effects and entry year fixed effects. Reference education for the parents is vocational college. Prior earnings are measured in 10,000 euro (deflated).

Table A2 – Descriptive Statistics for Unmatched Sample (Treated vs. Full Control)

	(1)	(2)	(3)	(4)	(5)	(6)
	Mean					V(T)/
Variable	Entrants	Non-Entrants	%bias	t-test	p-value	V(C)
Earnings at t - 10	13.024	7.390	46.2	43.9	0.000	1.55
Earnings at t - 9	14.805	8.785	47.0	43.7	0.000	1.45
Earnings at t - 8	16.787	10.533	46.6	42.4	0.000	1.34
Earnings at t - 7	18.845	12.468	45.5	40.7	0.000	1.27
Earnings at t - 6	21.563	14.488	48.5	42.6	0.000	1.18
Earnings at t - 5	24.788	16.658	54.2	46.2	0.000	1.05
Earnings at t - 4	28.405	19.131	60.8	50.0	0.000	0.91
Earnings at t - 3	32.017	21.968	65.7	52.0	0.000	0.76
Earnings at t - 2	34.674	25.061	61.7	48.6	0.000	0.75
Earnings at t - 1	36.806	28.055	54.6	43.6	0.000	0.79
Earnings at t	38.185	30.133	48.6	38.9	0.000	0.81
Employed at t - 10	0.537	0.344	39.7	34.2	0.000	.
Employed at t - 9	0.609	0.407	41.4	34.7	0.000	.
Employed at t - 8	0.669	0.476	39.6	32.4	0.000	.
Employed at t - 7	0.718	0.545	36.4	29.2	0.000	.
Employed at t - 6	0.782	0.603	39.6	30.9	0.000	.
Employed at t - 5	0.848	0.658	45.1	33.8	0.000	.
Employed at t - 4	0.913	0.721	51.4	36.2	0.000	.
Employed at t - 3	0.956	0.783	52.9	35.3	0.000	.
Employed at t - 2	0.969	0.843	44.0	29.2	0.000	.
Employed at t - 1	0.975	0.888	35.0	23.3	0.000	.
Age in years	36.614	32.818	53.3	47.1	0.000	1.21
Female	0.631	0.614	3.6	3.1	0.002	.
Finnish speaker	0.963	0.955	4.0	3.2	0.001	.
Swedish speaker	0.025	0.033	-5.3	-4.2	0.000	.
Other language	0.013	0.012	0.9	0.8	0.444	.
Not living in the region of birth	0.445	0.428	3.4	2.9	0.004	.
Enrolled in any education, t - 1	0.066	0.068	-0.7	-0.6	0.556	.
Enrolled in any education, t - 2	0.113	0.220	-28.8	-21.7	0.000	.
Enrolled in university education, t - 1	0.017	0.008	8.2	8.6	0.000	.
Enrolled in university education, t - 2	0.021	0.009	9.5	10.1	0.000	.
BA-degree from business	0.257	0.282	-5.7	-4.7	0.000	.
BA-degree from tech & trades	0.259	0.272	-2.8	-2.4	0.019	.
BA-degree from health care	0.347	0.288	12.5	10.8	0.000	.
BA-degree from other fields	0.137	0.158	-5.8	-4.8	0.000	.
Years from BA-degree to entry	5.562	4.462	41.5	33.2	0.000	0.80

Table A2 (Continued)

Variable	(1) Mean Entrants	(2) Mean Non-Entrants	(3) %bias	(4) t-test	(5) p-value	(6) V(T)/ V(C)
No. of degree-leading education programs attended in 7 years						
- Zero programs	0.783	0.708	17.1	13.7	0.000	.
- One program	0.171	0.167	1.1	0.9	0.374	.
- Two or more	0.046	0.124	-28.2	-20.0	0.000	.
Study loan (€1,000)	0.893	1.522	-23.1	-17.1	0.000	0.53
Comprehensive school grade (4-10)	5.936	6.820	-27.6	-26.1	0.000	1.53
Comprehensive school grade missing	0.255	0.142	28.7	27.3	0.000	.
Has graduated from high school	0.701	0.734	-7.4	-6.3	0.000	.
Exam score in native language						
Not written or failed	0.289	0.259	6.9	5.9	0.000	.
1	0.029	0.035	-3.3	-2.7	0.007	.
2	0.103	0.107	-1.3	-1.1	0.274	.
3	0.262	0.286	-5.4	-4.5	0.000	.
4	0.227	0.223	1.0	0.8	0.408	.
5	0.090	0.091	-0.2	-0.2	0.859	.
Exam score in English language						
Not written or failed	0.302	0.270	7.0	6.0	0.000	.
1	0.111	0.116	-1.5	-1.3	0.197	.
2	0.186	0.190	-1.0	-0.9	0.383	.
3	0.194	0.198	-0.9	-0.8	0.431	.
4	0.130	0.141	-3.1	-2.5	0.011	.
5	0.077	0.085	-3.0	-2.5	0.013	.
Exam score in mathematics						
Not written or failed	0.487	0.472	3.0	2.5	0.012	.
1	0.097	0.094	1.2	1.0	0.324	.
2	0.128	0.129	-0.4	-0.4	0.727	.
3	0.133	0.139	-1.9	-1.6	0.115	.
4	0.096	0.103	-2.2	-1.9	0.063	.
5	0.059	0.063	-1.6	-1.3	0.189	.
Married	0.812	0.738	17.8	14.2	0.000	.
Has child	0.302	0.318	-3.5	-2.9	0.004	.
Spouse employed	0.682	0.615	14.1	11.6	0.000	.
Spouse’s taxable income	2.511	2.131	11.4	8.1	0.000	0.42

Table A2 (Continued)

Variable	(1) Mean Entrants	(2) Mean Non-Entrants	(3) %bias	(4) t-test	(5) p-value	(6) V(T)/ V(C)
Mother's education						
Vocational college	0.119	0.140	-6.2	-5.1	0.000	.
Lower tertiary	0.062	0.074	-4.6	-3.7	0.000	.
Master's	0.045	0.052	-3.2	-2.6	0.010	.
Doctorate	0.007	0.008	-0.7	-0.6	0.538	.
Basic/Unknown	0.477	0.409	13.8	11.7	0.000	.
High school	0.011	0.013	-1.9	-1.5	0.130	.
Vocational school	0.278	0.304	-5.8	-4.8	0.000	.
Father's education						
Vocational college	0.144	0.175	-8.5	-6.9	0.000	.
Lower tertiary	0.043	0.049	-2.7	-2.2	0.029	.
Master's	0.025	0.031	-3.6	-2.9	0.003	.
Doctorate	0.002	0.002	-1.6	-1.3	0.202	.
Basic/Unknown	0.431	0.359	14.9	12.8	0.000	.
High school	0.018	0.022	-2.8	-2.2	0.025	.
Vocational school	0.337	0.362	-5.3	-4.4	0.000	.
Mother entrepreneur, not farmer (in '85 or '95)	0.121	0.132	-3.3	-2.7	0.006	.
Mother employee in prof. occ. (in '85 or '95)	0.536	0.593	-11.5	-9.8	0.000	.
Father entrepreneur, not farmer (in '85 or '95)	0.173	0.186	-3.2	-2.7	0.008	.
Father employee in prof. occ. (in '85 or '95)	0.337	0.385	-10.1	-8.4	0.000	.
Unempl. rate	0.098	0.103	-12.1	-9.9	0.000	0.89
Living in Helsinki region	0.292	0.323	-6.8	-5.6	0.000	.
Number of obs.	7,148	766,405				

Notes: Data also include dummies for region of residence prior to entry (NUTS-3) and entry year. Earnings are measured in 1,000 euro. V(T) / V(C) indicates the variance ratio (for continuous covariates) of treated over non-treated. Ratio should be equal to 1 for perfect balance.

Table A3 – Descriptive Statistics for Matched Sample (Treated vs. Matched Control)

	(1)	(2)	(3)	(4)	(5)	(6)
	Mean					V(T)/
Variable	Entrants	Non-Entrants	%bias	t-test	p-value	V(C)
Earnings at t - 10	13.024	12.945	0.7	0.4	0.724	1.01
Earnings at t - 9	14.805	14.705	0.8	0.4	0.670	0.99
Earnings at t - 8	16.787	16.685	0.8	0.4	0.669	1.01
Earnings at t - 7	18.845	18.872	-0.2	-0.1	0.911	1.00
Earnings at t - 6	21.563	21.704	-1.0	-0.6	0.579	1.00
Earnings at t - 5	24.788	24.859	-0.5	-0.3	0.780	0.98
Earnings at t - 4	28.405	28.427	-0.1	-0.1	0.928	0.95
Earnings at t - 3	32.017	31.957	0.4	0.3	0.804	0.91
Earnings at t - 2	34.674	34.750	-0.5	-0.3	0.756	0.97
Earnings at t - 1	36.806	36.870	-0.4	-0.3	0.803	0.94
Earnings at t	38.185	38.163	0.1	0.1	0.933	0.95
Employed at t - 10	0.537	0.538	-0.2	-0.1	0.907	.
Employed at t - 9	0.609	0.613	-0.8	-0.5	0.625	.
Employed at t - 8	0.669	0.669	0.0	0.0	0.979	.
Employed at t - 7	0.718	0.720	-0.5	-0.3	0.738	.
Employed at t - 6	0.782	0.787	-1.1	-0.8	0.452	.
Employed at t - 5	0.848	0.846	0.4	0.3	0.771	.
Employed at t - 4	0.913	0.917	-1.0	-0.8	0.435	.
Employed at t - 3	0.956	0.959	-1.2	-1.1	0.264	.
Employed at t - 2	0.969	0.971	-0.7	-0.7	0.511	.
Employed at t - 1	0.975	0.978	-0.9	-0.9	0.363	.
Age in years	36.614	36.650	-0.5	-0.3	0.771	1.00
Female	0.631	0.632	-0.3	-0.2	0.876	.
Finnish speaker	0.963	0.964	-0.7	-0.5	0.656	.
Swedish speaker	0.025	0.024	0.4	0.2	0.807	.
Other language	0.013	0.012	0.7	0.4	0.677	.
Not living in the region of birth	0.445	0.448	-0.7	-0.4	0.662	.
Enrolled in any education, t - 1	0.066	0.059	2.8	1.7	0.082	.
Enrolled in any education, t - 2	0.113	0.104	2.5	1.8	0.079	.
Enrolled in university education, t - 1	0.017	0.016	1.1	0.6	0.575	.
Enrolled in university education, t - 2	0.021	0.021	-0.2	-0.1	0.931	.
BA-degree from business	0.257	0.260	-0.8	-0.5	0.647	.
BA-degree from tech & trades	0.259	0.254	1.3	0.8	0.444	.
BA-degree from health care	0.347	0.347	0.0	0.0	0.986	.
BA-degree from other fields	0.137	0.139	-0.7	-0.4	0.680	.
Years from BA-degree to entry	5.562	5.644	-3.1	-2.0	0.050	1.01

Table A3 (Continued)

Variable	(1) Mean Entrants	(2) Non-Entrants	(3) %bias	(4) t-test	(5) p-value	(6) V(T)/V(C)
No. of degree-leading education programs attended in 7 years						
- Zero programs	0.783	0.784	-0.4	-0.3	0.792	.
- One program	0.171	0.170	0.3	0.2	0.868	.
- Two or more	0.046	0.046	0.3	0.2	0.826	.
Study loan (€1,000)	0.893	0.889	0.2	0.1	0.900	0.99
Comprehensive school grade (4-10)	5.936	5.956	-0.6	-0.3	0.734	1.01
Comprehensive school grade missing	0.255	0.252	0.7	0.4	0.701	.
Has graduated from high school	0.701	0.709	-1.6	-1.0	0.340	.
Exam score in native language						
Not written or failed	0.289	0.281	1.7	1.0	0.304	.
1	0.029	0.028	0.3	0.2	0.861	.
2	0.103	0.103	-0.1	0.0	0.967	.
3	0.262	0.266	-1.1	-0.7	0.519	.
4	0.227	0.235	-1.7	-1.0	0.307	.
5	0.090	0.086	1.4	0.8	0.408	.
Exam score in English language						
Not written or failed	0.302	0.295	1.5	0.9	0.361	.
1	0.111	0.111	0.0	0.0	0.979	.
2	0.186	0.189	-0.6	-0.4	0.700	.
3	0.194	0.197	-0.7	-0.4	0.666	.
4	0.130	0.132	-0.4	-0.3	0.804	.
5	0.077	0.077	-0.1	-0.1	0.937	.
Exam score in mathematics						
Not written or failed	0.487	0.486	0.1	0.1	0.933	.
1	0.097	0.097	0.0	0.0	0.977	.
2	0.128	0.130	-0.5	-0.3	0.745	.
3	0.133	0.132	0.1	0.1	0.941	.
4	0.096	0.092	1.3	0.8	0.423	.
5	0.059	0.063	-1.4	-0.8	0.402	.
Married	0.812	0.810	0.5	0.3	0.749	.
Has child	0.302	0.304	-0.5	-0.3	0.750	.
Spouse employed	0.682	0.679	0.6	0.4	0.726	.
Spouse’s taxable income	2.511	2.524	-0.4	-0.3	0.779	0.84

Table A3 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	Mean					
Variable	Entrants	Non-Entrants	%bias	t-test	p-value	V(T)/ V(C)
Mother's education						
Vocational college	0.144	0.142	0.5	0.3	0.756	.
Lower tertiary	0.043	0.045	-0.8	-0.5	0.610	.
Master's	0.025	0.025	-0.1	-0.1	0.936	.
Doctorate	0.002	0.002	0.0	0.0	1.000	.
Basic/Unknown	0.431	0.428	0.7	0.4	0.691	.
High school	0.018	0.017	0.7	0.5	0.655	.
Vocational school	0.337	0.341	-0.9	-0.5	0.602	.
Father's education						
Vocational college	0.119	0.118	0.2	0.1	0.887	.
Lower tertiary	0.062	0.061	0.6	0.4	0.702	.
Master's	0.045	0.043	0.7	0.4	0.684	.
Doctorate	0.007	0.007	0.4	0.3	0.801	.
Basic/Unknown	0.477	0.479	-0.3	-0.2	0.841	.
High school	0.011	0.011	0.6	0.4	0.718	.
Vocational school	0.278	0.281	-0.7	-0.4	0.689	.
Mother entrepreneur, not farmer (in '85 or '95)	0.121	0.124	-0.7	-0.4	0.665	.
Mother employee in prof. occ. (in '85 or '95)	0.536	0.542	-1.2	-0.7	0.460	.
Father entrepreneur, not farmer (in '85 or '95)	0.173	0.173	0.1	0.1	0.930	.
Father employee in prof. occ. (in '85 or '95)	0.337	0.329	1.7	1.0	0.303	.
Unempl. rate	0.098	0.098	0.0	0.0	0.982	0.96
Living in Helsinki region	0.292	0.295	-0.7	-0.5	0.653	.
Number of obs.	7,148	13,923				

Notes: Data also include dummies for region of residence prior to entry (NUTS-3) and entry year. Earnings are measured in 1,000 euro. V(T) / V(C) indicates the variance ratio (for continuous covariates) of treated over non-treated. Ratio should be equal to 1 for perfect balance.

Table A4 – Alternative Coarsened Exact Matching (CEM) Estimator Results by Year Relative to Entry (with 95% Confidence Intervals)

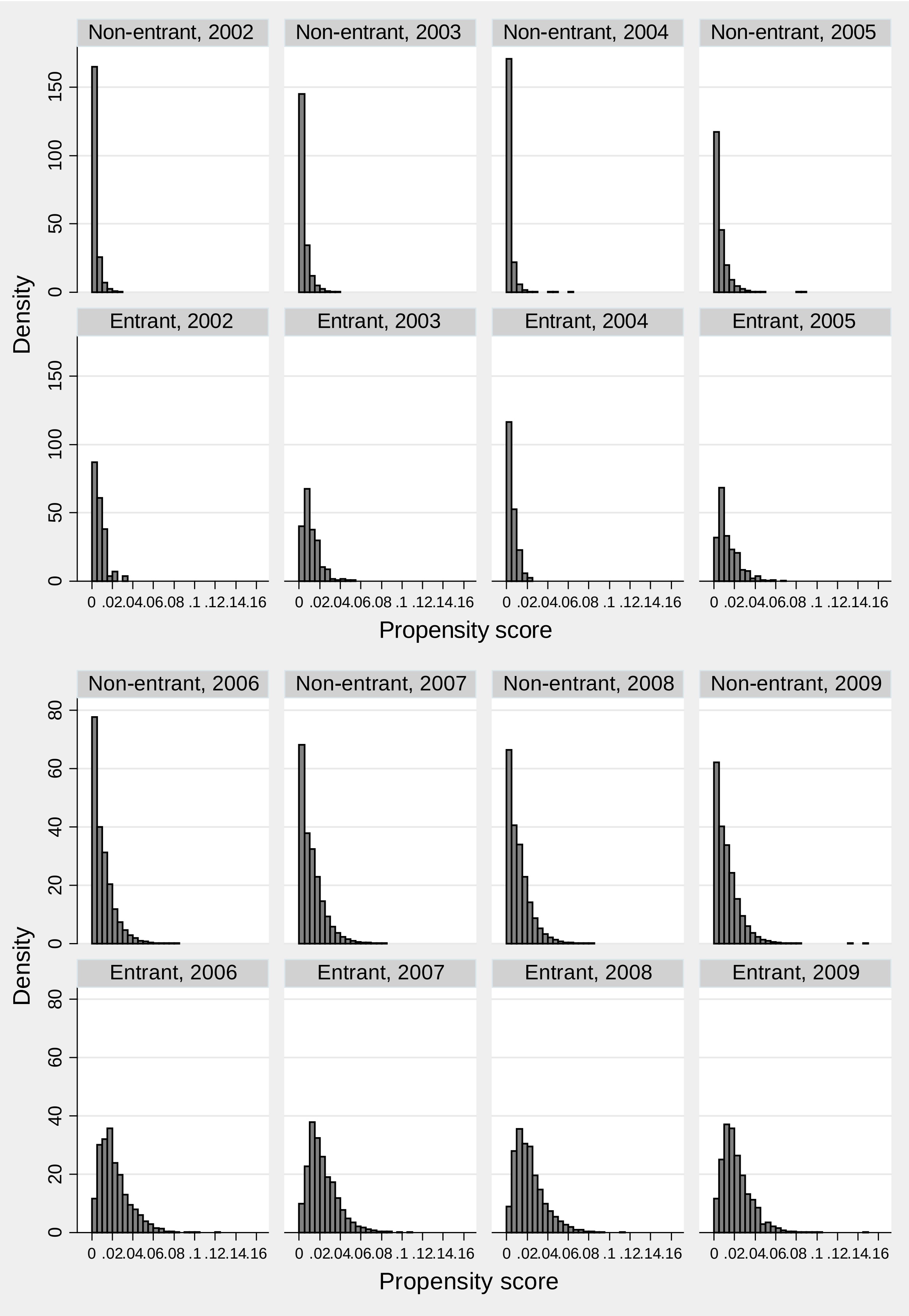
	Annual Earnings		Annual Employment	
	(1)	(2)	(3)	(4)
Time Since Entry	Excl. Year 0 Earnings	Incl. Year 0 Earnings	Excl. Year 0 Earnings	Incl. Year 0 Earnings
-10	0.443**	0.508**	0.004	0.006
-9	0.343	0.335	0.006	0.003
-8	0.290	0.190	0.002	0.001
-7	0.088	0.134	0.000	0.002
-6	0.195	0.170	-0.004	-0.005
-5	0.244	0.267	-0.002	-0.002
-4	0.090	0.045	-0.002	0.000
-3	0.284	0.157	0.002	-0.001
-2	0.337	0.225	0.002	0.003
-1	0.336	0.164	0.000	0.000
0	1.170***	0.018	-0.003	-0.008***
1	0.997***	0.116	-0.007***	-0.010***
2	1.852***	1.117***	0.002	-0.004
3	2.570***	1.996***	-0.001	-0.003
4	3.308***	2.859***	0.007**	0.007**
5	3.519***	3.145***	0.004	0.005
6	3.567***	3.453***	0.011***	0.013***
7	4.162***	3.931***	0.019***	0.025***
8	4.483***	4.601***	0.006	0.007
Number of entrants with exact match at t-1	5,080	4,399	5,080	4,399
Exactly matched, %	71.1%	61.5%	71.1%	61.5%

Notes: Total number of entrants is 7,148. Statistical significance in two-sided tests are denoted by * for the ten-percent level, ** for the five-percent level, and *** for the one-percent level.

Two different CEM specifications are reported:

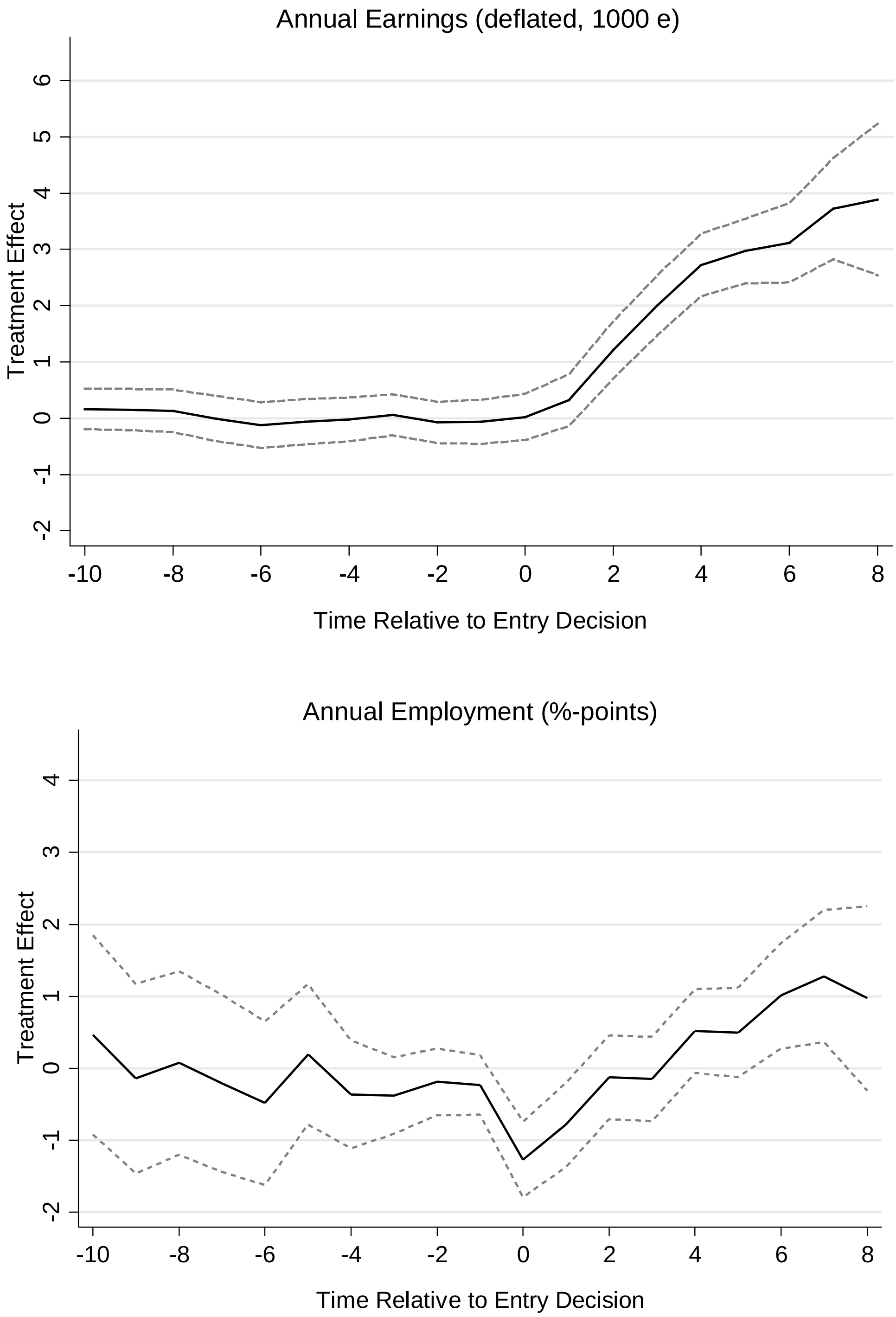
- In columns (1) and (3), model is implemented using i) quartiles of average earnings in t-10, … , t-7; ii) quartiles of average earnings in t-6,…, t-4; iii) quartiles of average earnings in t-3 and t-2; iv) quartiles of earnings in t-1; v) sum of employment status (1/0) in t-10,…, t-6; vi) sum of employment status (1/0) in t-5,…, t-2; vii) employed in t-1; viii) three age groups 25-29, 30-34 and 35-55; ix) sex; x) enrolled in education in t-1 or t-2; xi) years from BA-degree to entry (three categories); xii) prior field of education (four categories); xiii) three regional categories; xiv) year of entry.
- In columns (2) and (4), we add quartiles of year 0 earnings

Figure A1 – Common Support for 2002–2009 (Densities)



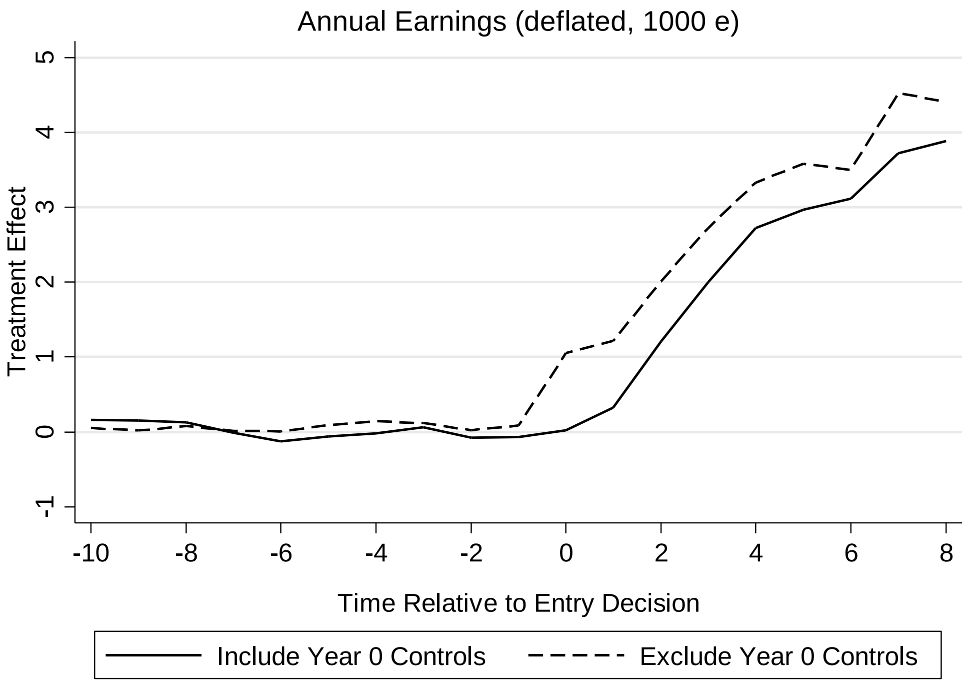
Notes: A probit model is used to estimate the propensity scores (see Table A1 for results).

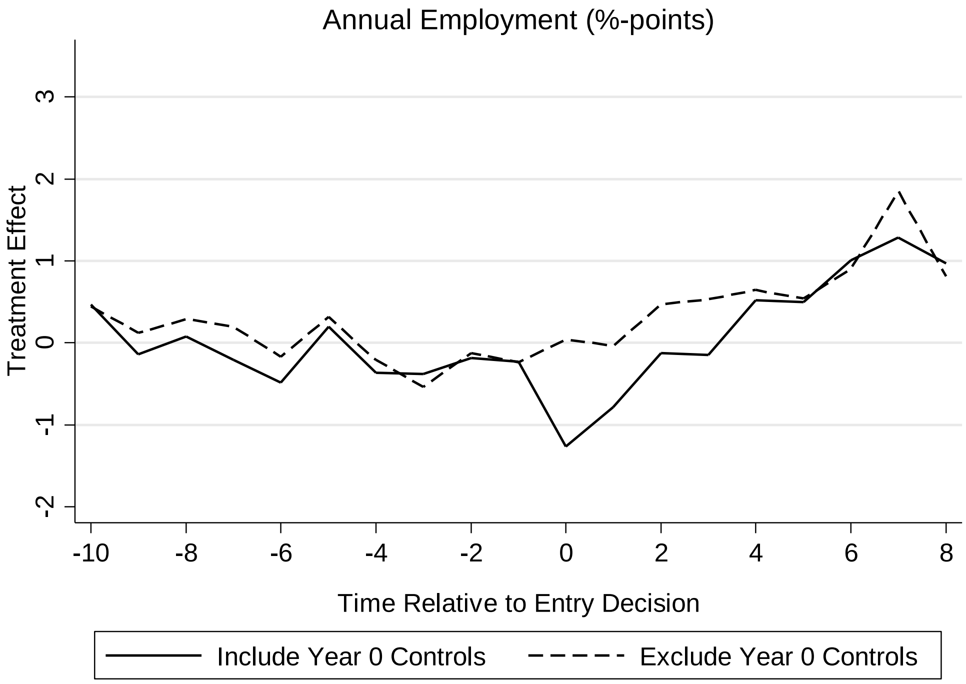
Figure A2 – Matching Estimator Results by Year Relative to Entry
(with 95% Confidence Intervals)



Notes: The results are based on propensity score matching on two nearest neighbors on common support with exact matching on the entry year. A probit model is used to estimate the propensity scores (the results are available on Table A1). Dashed lines indicate 95% confidence intervals based on Abadie and Imbens (2016) robust standard errors.

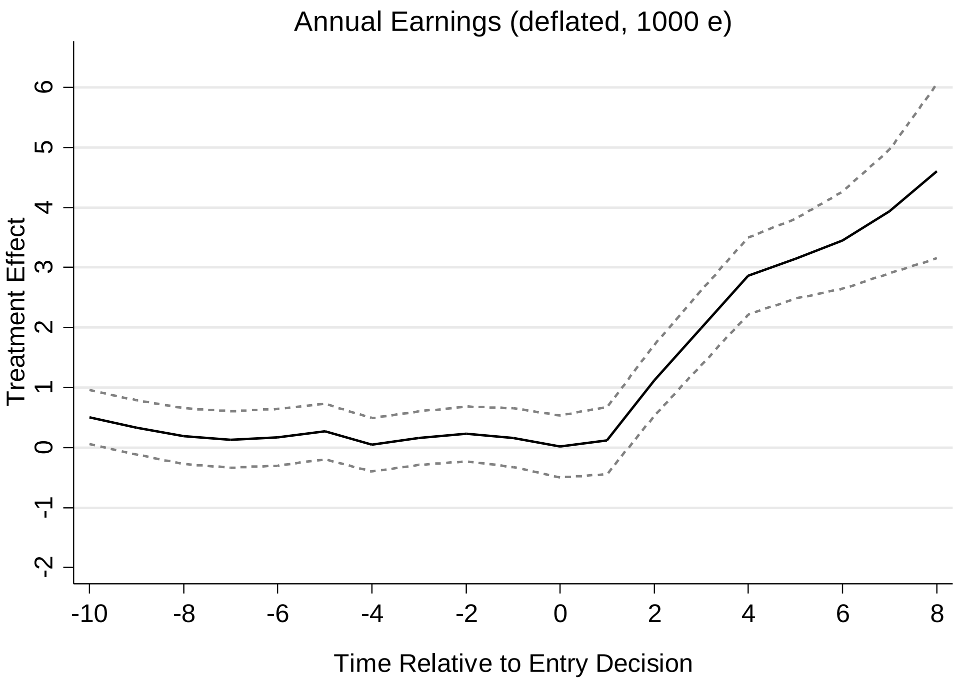
Figure A3 – Differences in Outcomes for Matching Analysis

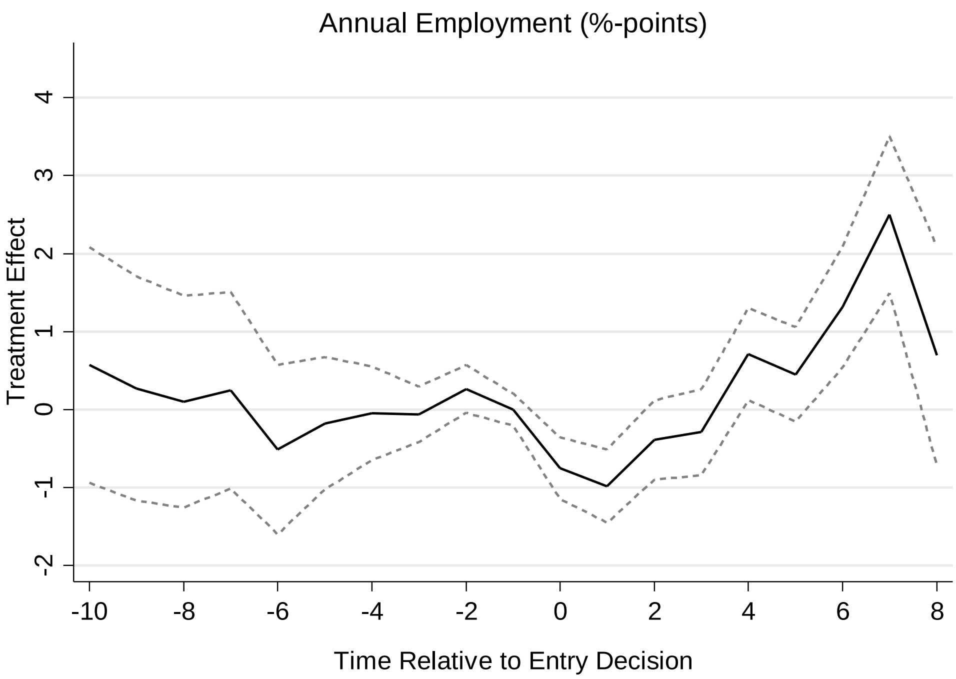




Notes: Number of entrants 7,148 and the number of matched non-entrants is 13,923 (from 766,405 non-entrants in common support). Average treatment effects on the treated are reported. The results are based on propensity score matching on two nearest neighbors on common support with exact matching on the entry year. A probit model is used to estimate the propensity scores (see Table 1 for the baseline).

Figure A4 – Coarsened Exact Matching (CEM) Estimator Results by Year Relative to Entry (with 95% Confidence Intervals)





Notes: See Table A4 (columns 2 and 4) for the specification of the model. Exact match is found for 61.5% of the 7,148 polytechnic entrants.

B) Additional Estimation Tables and Figures

Table B1 – Discounted Cumulative Earnings Gains from Attending Polytechnic Education (€1,000)

Time Since Entry	Raw	Discounted	Cumulated
0	0.080	0.080	0.080
1	0.380	0.365	0.445
2	1.274	1.178	1.623
3	2.077	1.846	3.470
4	2.804	2.397	5.867
5	3.047	2.504	8.371
6	3.167	2.503	10.874
7	3.624	2.754	13.628
8	4.169	3.046	16.674
Total Gains 0-8	20.622	16.674	

Notes: Calculations use fixed effects regression results on the matched sample reported in Figure 2 and Table 2. Following Koedel and Podgursky (2016), we use the discount rate of 4%.

Table B2 – Fixed Effect Returns by Change of Employer (Matched Sample)

	Annual Earnings		Annual Employment	
	(1)	(2)	(3)	(4)
Time Since Entry	Employer Changed	Not Changed	Employer Changed	Not Changed
Entry year	0.139	0.011	-0.00918**	-0.00555**
	(0.185)	(0.168)	(0.00420)	(0.00230)
1 year after entry	0.539**	0.214	-0.00737*	-0.00718***
	(0.256)	(0.221)	(0.00445)	(0.00274)
2 years after entry	1.722***	0.900***	0.00486	-0.00290
	(0.300)	(0.253)	(0.00401)	(0.00243)
3 years after entry	2.367***	1.668***	0.00040	0.00007
	(0.318)	(0.274)	(0.00129)	(0.00044)
4 years after entry	3.299***	2.340***	0.00711*	0.00907***
	(0.338)	(0.310)	(0.00386)	(0.00291)
5 years after entry	3.735***	2.568***	0.00396	0.00900**
	(0.372)	(0.341)	(0.00448)	(0.00364)
6 years after entry	3.918***	2.758***	0.01414***	0.00707
	(0.451)	(0.419)	(0.00522)	(0.00492)
7 years after entry	3.942***	3.246***	0.01433**	0.01605**
	(0.555)	(0.537)	(0.00639)	(0.00643)
8 years after entry	4.294***	3.218***	0.00682	0.01450
	(0.822)	(0.744)	(0.00811)	(0.00910)
Number of observations	177,133	166,508	177,133	166,508
Number of individuals	9,604	9,220	9,604	9,220
Adjusted R-squared	0.687	0.721	0.358	0.362

Notes: * = significant at 10%; ** = significant at 5%; *** = significant at 1% (all two-sided tests). Standard errors are in parentheses. Each column contains the results from a separate regression. The regressions also include controls for time relative to entry (not interacted with treatment status), dummy variables for calendar year, and age in years as listed in equation (2). The estimated coefficients for the periods prior to entry are not reported. Estimations are based on sample of attendants and matched non-attendants. Annual earnings are measured in 1,000 euro (deflated). Employer change is measured in t-1 and t+3. Estimates are conditional on being employed in t-1 and t+3.

Table B3 – Changes in Occupational Level Before and After Entry Decision in 2005–2009

Occupational Level	Entry Year (t)	After Entry (t+1)	After Entry (t+3)	After Entry (t+5)
(1) Treated				
- Moved up	7.5 %	12.5 %	19.5 %	24.0 %
- Remained the same	87.1 %	78.9 %	68.8 %	63.3 %
- Moved down	5.4 %	8.6 %	11.7 %	12.7 %
	100%	100%	100%	100%
(2) Matched Controls				
- Moved up	5.8 %	8.7 %	11.8 %	14.2 %
- Remained the same	89.4 %	83.8 %	78.0 %	74.6 %
- Moved down	4.7 %	7.5 %	10.2 %	11.2 %
	100%	100%	100%	100%
Difference (1)–(2)				
- Moved up	1.7 %	3.8 %	7.6 %	9.8 %
- Remained the same	-2.3 %	-4.9 %	-9.2 %	-11.3 %
- Moved down	0.6 %	1.1 %	1.6 %	1.5 %
	0%	0%	0%	0%

Notes: Number of entrants is 6,624. They have been matched to the non-entrants using propensity score model specification reported in Table A1. Occupation is compared to the year before entry (t-1) using three levels: 1) Managers (highest level); 2) Professionals; 3) Other occupations (lowest level). We utilize Statistics Finland’s Classification of Occupations 2001 and 2010 that closely follow the international ISCO-88 and ISCO-08 classifications. Occupation is known annually for 2004–2014, and therefore we only use cohorts from 2005–2009.

Table B4 – Fixed Effect Earnings Returns to Program Attendance (Matched Sample): Dependent Variable Is Log of Annual Earnings

Variable	Full Sample	Gender: Females	Gender: Males
Attendees - Entry year	0.000	0.006	0.001
	(0.007)	(0.010)	(0.008)
Attendees - 1 year after entry	0.020**	0.049***	-0.003
	(0.009)	(0.013)	(0.011)
Attendees - 2 years after entry	0.038***	0.077***	0.002
	(0.010)	(0.015)	(0.012)
Attendees - 3 years after entry	0.061***	0.089***	0.040***
	(0.011)	(0.015)	(0.013)
Attendees - 4 years after entry	0.079***	0.111***	0.061***
	(0.011)	(0.016)	(0.014)
Attendees - 5 years after entry	0.082***	0.107***	0.065***
	(0.012)	(0.016)	(0.015)
Attendees - 6 years after entry	0.086***	0.112***	0.070***
	(0.014)	(0.019)	(0.018)
Attendees - 7 years after entry	0.091***	0.120***	0.085***
	(0.016)	(0.022)	(0.022)
Attendees - 8 years after entry	0.107***	0.134***	0.109***
	(0.020)	(0.027)	(0.028)
Number of observations	353,736	222,135	131,363
Number of individuals	19,597	12,469	7,378
Adjusted R-squared	0.562	0.501	0.648

Notes: * = significant at 10%; ** = significant at 5%; *** = significant at 1% (all two-sided tests). Standard errors are in parentheses. Each column contains the results from a separate regression. The regressions also include controls for time relative to entry (not interacted with treatment status), dummy variables for calendar year, and age in years as listed in equation (2). Dependent variable is log of annual earnings in 1,000 euro (deflated). All pre-treatment effects (t = -10,…, -1) are insignificant at $p < 0.1$, except for the effect for full sample at t = -4 (significant at 10%).

Table B5 – Fixed Effect Returns to Program Attendance (Matched Sample): Excluding Individuals Attending Universities after Entry Decision

	Annual Earnings		Annual Employment	
Variable	Coeff.	Std. Err.	Coeff.	Std. Err.
Attendees - Entry year	0.044	0.133	-0.00952***	0.00318
Attendees - 1 year after entry	0.196	0.181	-0.00866**	0.00351
Attendees - 2 years after entry	1.284***	0.211	0.00055	0.00360
Attendees - 3 years after entry	1.991***	0.231	-0.00125	0.00374
Attendees - 4 years after entry	2.611***	0.248	0.00367	0.00371
Attendees - 5 years after entry	3.006***	0.265	0.00596	0.00390
Attendees - 6 years after entry	3.000***	0.319	0.00797*	0.00443
Attendees - 7 years after entry	3.418***	0.394	0.00832	0.00536
Attendees - 8 years after entry	3.845***	0.597	0.00329	0.00709
Attendees - 2 years before entry	0.045	0.129	-0.00200	0.00295
Attendees - 3 years before entry	0.165	0.166	0.00141	0.00363
Attendees - 4 years before entry	0.087	0.192	-0.00092	0.00466
Attendees - 5 years before entry	0.064	0.207	-0.00027	0.00560
Attendees - 6 years before entry	0.244	0.217	0.00256	0.00625
Attendees - 7 years before entry	0.262	0.223	0.00576	0.00669
Attendees - 8 years before entry	0.137	0.231	0.00566	0.00697
Attendees - 9 years before entry	0.122	0.233	0.00201	0.00709
Attendees - 10 years before entry	0.174	0.243	0.00270	0.00729
Number of observations	346,007		346,007	
Number of individuals	18,526		18,526	
Adjusted R-squared	0.688		0.346	

Notes: * = significant at 10%; ** = significant at 5%; *** = significant at 1% (all two-sided tests). The regressions also include controls for time relative to entry (not interacted with treatment status), dummy variables for calendar year, and age in years as listed in equation (2). Estimations are based on sample of attendants and matched non-attendants. Annual earnings are measured in 1,000 euro (deflated).

Table B6 – Returns to Program Attendance (Matched Sample): Gradually Excluding Controls from the Regression Model

	Annual Earnings				Annual Employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Baseline	Drop FEs	Drop FEs & Age	Drop FEs, Age & Year	Baseline	Drop FEs	Drop FEs & Age	Drop FEs Age & Year
Attendees - Entry year	0.080	0.014	0.022	0.022	-0.010***	-0.012***	-0.013***	-0.013***
	(0.129)	(0.230)	(0.234)	(0.234)	(0.003)	(0.003)	(0.003)	(0.003)
Attendees - 1 year after entry	0.380**	0.317	0.324	0.324	-0.006	-0.008**	-0.008***	-0.008***
	(0.175)	(0.253)	(0.257)	(0.257)	(0.003)	(0.003)	(0.003)	(0.003)
Attendees - 2 years after entry	1.274***	1.213***	1.211***	1.211***	0.001	-0.001	-0.001	-0.001
	(0.205)	(0.271)	(0.276)	(0.276)	(0.004)	(0.003)	(0.003)	(0.003)
Attendees - 3 years after entry	2.077***	2.019***	2.005***	2.005***	0.001	-0.001	-0.001	-0.001
	(0.225)	(0.284)	(0.289)	(0.289)	(0.004)	(0.003)	(0.003)	(0.003)
Attendees - 4 years after entry	2.804***	2.746***	2.725***	2.725***	0.008**	0.005*	0.005*	0.005*
	(0.242)	(0.294)	(0.298)	(0.298)	(0.004)	(0.003)	(0.003)	(0.003)
Attendees - 5 years after entry	3.047***	2.997***	2.975***	2.975***	0.007*	0.005	0.005	0.005
	(0.258)	(0.304)	(0.308)	(0.308)	(0.004)	(0.003)	(0.003)	(0.003)
Attendees - 6 years after entry	3.167***	3.168***	3.131***	3.131***	0.012***	0.010***	0.011***	0.011***
	(0.311)	(0.370)	(0.374)	(0.374)	(0.004)	(0.004)	(0.004)	(0.004)
Attendees - 7 years after entry	3.624***	3.806***	3.737***	3.737***	0.014***	0.013***	0.013***	0.013***
	(0.382)	(0.468)	(0.472)	(0.472)	(0.005)	(0.005)	(0.005)	(0.005)
Attendees - 8 years after entry	4.169***	3.979***	3.930***	3.931***	0.013*	0.009	0.011*	0.011*
	(0.563)	(0.680)	(0.683)	(0.683)	(0.007)	(0.006)	(0.006)	(0.006)
Number of observations	367,791	367,791	367,791	367,791	367,791	367,791	367,791	367,791
Number of individuals	19,602	19,602	19,602	19,602	19,602	19,602	19,602	19,602
Adjusted R-squared	0.686	0.338	0.262	0.259	0.344	0.252	0.156	0.149

Notes: * = significant at 10%; ** = significant at 5%; *** = significant at 1% (all two-sided tests). Standard errors are in parentheses. Estimations are based on sample of attendants and matched non-attendants. Each column contains the results from a separate regression. Annual earnings are measured in 1,000 euro (deflated). Baseline models shown in columns (1) and (5) include individual fixed effects (FEs) as well as controls for time relative to entry (not interacted with treatment status), dummy variables for calendar year, and age in years as listed in equation (2) and reported in Table 2. Columns (2) and (6) exclude FEs, columns (3) and (7) exclude FEs and age dummies, and columns (4) and (8) exclude FEs and age and calendar year dummies. All models also include pre-treatment effects, but they are not reported for brevity. These pre-treatment effects are insignificant in all models (columns 1–8) for all periods (t = -2,…, -10).

Table B7 – Fixed Effect Returns to Program Attendance (Matched Sample): Including the Full Set of Occupational and Industry Dummies in the Matching Model

	Annual Earnings		Annual Employment	
Variable	Coeff.	Std. Err.	Coeff.	Std. Err.
Attendees - Entry year	-0.014	0.129	-0.010***	0.003
Attendees - 1 year after entry	0.176	0.173	-0.013***	0.003
Attendees - 2 years after entry	1.037***	0.204	-0.005	0.003
Attendees - 3 years after entry	1.806***	0.226	-0.002	0.004
Attendees - 4 years after entry	2.529***	0.241	0.001	0.004
Attendees - 5 years after entry	2.792***	0.263	0.001	0.004
Attendees - 6 years after entry	2.764***	0.311	0.002	0.004
Attendees - 7 years after entry	3.059***	0.383	0.006	0.005
Attendees - 8 years after entry	3.364***	0.561	-0.000	0.007
Attendees - 2 years before entry	-0.101	0.124	-0.002	0.003
Attendees - 3 years before entry	0.125	0.160	-0.002	0.004
Attendees - 4 years before entry	0.093	0.185	-0.001	0.005
Attendees - 5 years before entry	0.204	0.200	0.006	0.005
Attendees - 6 years before entry	0.246	0.210	0.003	0.006
Attendees - 7 years before entry	0.143	0.218	0.002	0.006
Attendees - 8 years before entry	0.158	0.219	0.010	0.007
Attendees - 9 years before entry	0.101	0.225	0.008	0.007
Attendees - 10 years before entry	0.026	0.234	0.004	0.007
Number of observations	367,050		367,050	
Number of individuals	19,477		19,477	
Adjusted R-squared	0.685		0.349	

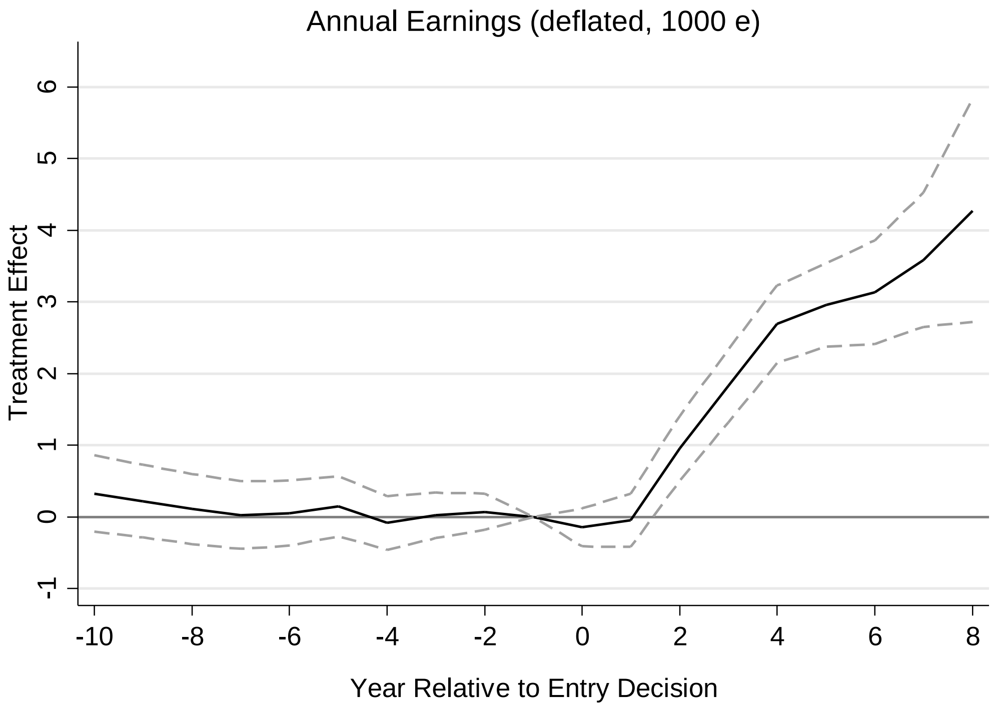
Notes: * = significant at 10%; ** = significant at 5%; *** = significant at 1% (all two-sided tests). Annual earnings are in 1,000 euro (deflated). The regressions also include controls for time relative to entry (not interacted with treatment status), dummy variables for calendar year, and age in years as listed in equation (2). Estimations are based on sample of attendants and matched non-attendants. The baseline matching model has been expanded with industry and occupational dummies. The employer's industry is measured using the standard Industrial Classification (2002) at the character level (sections A to Q, and X for unknown). Occupation dummies utilize ten major groups of Classification of Occupations (2001), which is based on EU's classification of occupations ISCO. Industry and occupation groups are measured for the most recent available year prior to decision to enter polytechnic.

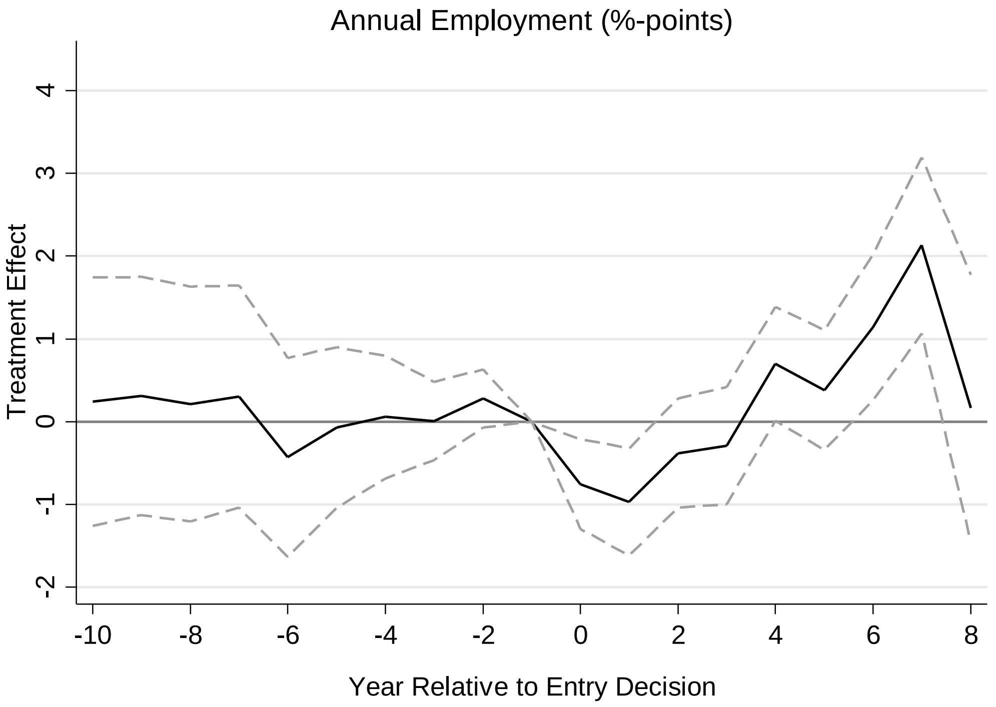
Table B8 – Placebo Regression Results Using Mother's Outcomes (Fixed Effect Results on the Matched Sample)

	Mother's Annual Earnings		Mother's Annual Employment	
Variable	Coeff.	Std. Err.	Coeff.	Std. Err.
Attendees - Entry year	0.170	(0.121)	-0.001	(0.005)
Attendees - 1 year after entry	0.013	(0.169)	-0.007	(0.006)
Attendees - 2 years after entry	-0.301	(0.204)	-0.011	(0.007)
Attendees - 3 years after entry	-0.231	(0.237)	-0.007	(0.008)
Attendees - 4 years after entry	-0.135	(0.275)	-0.006	(0.009)
Attendees - 5 years after entry	-0.060	(0.303)	-0.002	(0.009)
Attendees - 6 years after entry	0.061	(0.365)	-0.010	(0.011)
Attendees - 2 years before entry	0.048	(0.114)	0.000	(0.005)
Attendees - 3 years before entry	0.054	(0.166)	0.003	(0.006)
Attendees - 4 years before entry	0.145	(0.201)	0.002	(0.007)
Attendees - 5 years before entry	-0.236	(0.220)	-0.004	(0.008)
Attendees - 6 years before entry	-0.301	(0.234)	-0.011	(0.008)
Attendees - 7 years before entry	-0.370	(0.245)	-0.017**	(0.008)
Attendees - 8 years before entry	-0.349	(0.259)	-0.022**	(0.009)
Attendees - 9 years before entry	-0.440	(0.270)	-0.017*	(0.009)
Attendees - 10 years before entry	-0.433	(0.283)	-0.024**	(0.009)
Number of observations	230,417		230,417	
Number of individuals	14,211		14,211	
Adjusted R-squared	0.688		0.597	

Notes: * = significant at 10%; ** = significant at 5%; *** = significant at 1% (all two-sided tests). The regressions also include controls for time relative to entry (not interacted with treatment status), dummy variables for calendar year, and age in years as listed in equation (3). Estimations are based on sample of attendants and matched non-attendants. Annual earnings are measured in 1,000 euro (deflated). We restrict the sample to observations $t < 7$ due to increasing mothers' mortality over time.

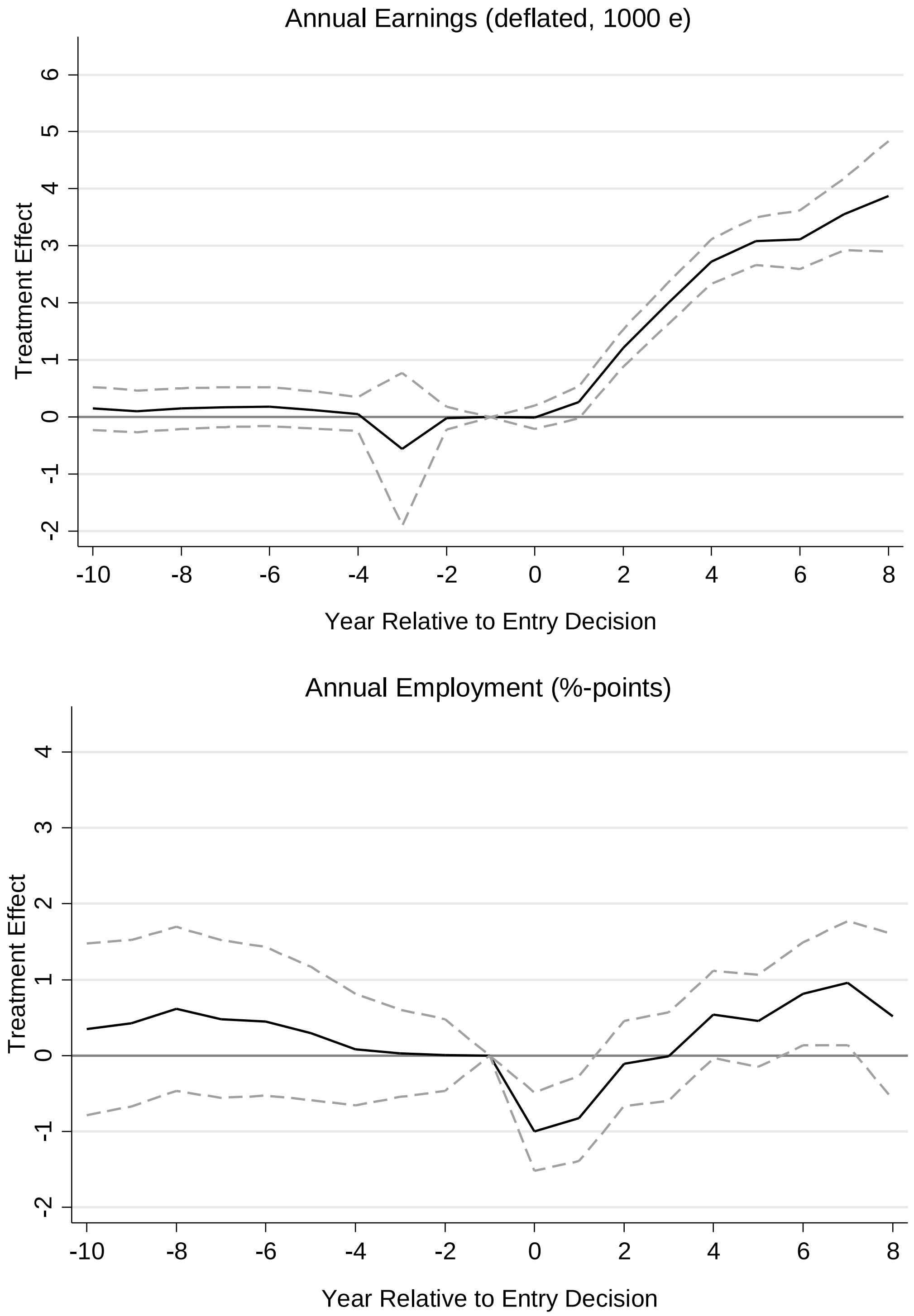
Figure B1 – Fixed Effects Returns to Program Attendance (with 95% Confidence Intervals): Estimated on Matched Data using CEM





Notes: See Table A4 (columns 2 and 4) for the specification of the CEM model. Exact match is found for 61.5% of the 7,148 polytechnic entrants. The matched fixed effects regressions also include controls for time relative to entry (not interacted with attendance status), dummy variables for calendar year, and age in years as listed in equation (2). Reference year is t-1.

Figure B2 – Fixed Effects Returns to Program Attendance (with 95% Confidence Intervals): Estimated using Inverse Probability Weighted Regression Models



Notes: Number of observations is 13,531,671. The inverse probability weighted (IPW) fixed effects regressions also include controls for time relative to entry (not interacted with attendance status), dummy variables for calendar year, and age in years as listed in equation (2). Reference year is t-1. The weights are 1 for the treated and $p(x_i)/(1–p(x_i))$ for the untreated. The propensity scores, $p(x_i)$, are estimated using probit model reported in Table A1.

C) Additional Descriptive Statistics and Information

Table C1 – Key Descriptive Statistics for Master's Students, including Dropouts vs. Completers

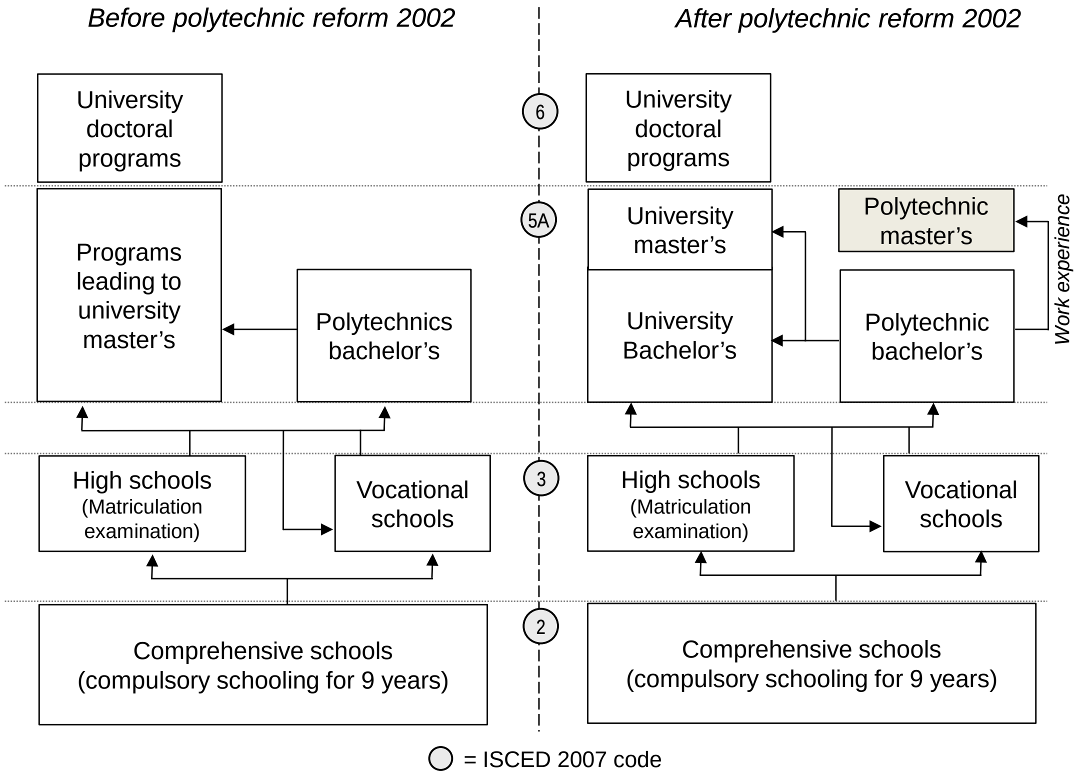
	(1)	(2)	(3)	(4)	(5)	(6)
	All Students		Dropouts		Completers	
	Mean	SD	Mean	SD	Mean	SD
Completion rate	0.710	0.454	0	0	1	0
Mean earnings, t-3, t-2, t-1	34.499	13.577	34.350	13.697	34.560	13.529
Mean earnings, t, t+1, t+2	39.018	15.835	39.135	16.037	38.970	15.754
Mean earnings, t+3, t+4, t+5	42.446	18.732	41.102	19.822	42.995	18.242
Mean earnings, t+6, t+7, t+8	45.262	22.541	42.889	27.815	46.213	19.974
Mean employment rate, t-3, t-2, t-1	0.966	0.127	0.964	0.128	0.967	0.127
Mean employment rate, t, t+1, t+2	0.956	0.151	0.949	0.160	0.959	0.148
Mean employment rate, t+3, t+4, t+5	0.955	0.165	0.943	0.179	0.959	0.158
Mean employment rate, t+6, t+7, t+8	0.953	0.172	0.933	0.202	0.962	0.158
Age at entry to polytechnic	36.614	7.446	35.843	7.202	36.929	7.522
Female	0.631	0.483	0.547	0.498	0.666	0.472
BA-degree from business-related fields [i]	0.257	0.437	0.280	0.449	0.248	0.432
BA-degree from tech & trades [i]	0.259	0.438	0.302	0.459	0.242	0.428
BA-degree from health care [i]	0.347	0.476	0.305	0.461	0.364	0.481
BA-degree from other fields [i]	0.137	0.344	0.114	0.318	0.147	0.354
Years from BA-degree to entry	5.562	2.497	5.655	2.392	5.523	2.538
Has graduated from high school [ii]	0.701	0.458	0.698	0.459	0.703	0.457
Living in Helsinki region [ii]	0.292	0.455	0.267	0.442	0.302	0.459
Number of students	7,148		5,073		2,075	

Notes: Earnings are measured in 1,000 euro (deflated to 2012). Completers (dropouts) are defined as entrants who (do not) graduate by 2014. [i] Field of education for the polytechnic bachelor's (BA) degree. [ii] Measured on the year prior to entry to polytechnic master's program.

Table contains descriptive statistics for the samples of master's students. The first two columns are for all attendees, the next two are for dropouts, and the following two are for completers. Immediately prior to entry, master's students have average earnings of approximately €36,800 in 2012 euros, with no difference between dropouts and completers. Three to five years after entry, their average earnings are around €42,500. During this period, average earnings are about €1,900 higher for completers than dropouts, a difference that is statistically different from zero at the one-percent level. Employment rates among attendees are at least 95 percent in each period starting three years before enrollment. As with earnings, completers have significantly higher employment 3–5 years after entry of nearly two percentage points relative to dropouts. For the entire sample, average age at entry is nearly 37 years old. Over 60 percent of enrollees are female, with an even higher percentage among completers.

Over 70 percent of students complete their master's degree. For the bachelor's degree, health care and welfare (typically nursing) is the most popular field of study (35 percent), followed by business-related fields (26 percent). On average, the entrants have completed their bachelor's (BA) degree from the polytechnics 5½ years prior to entry. Although not shown in the table, the number of people entering master's programs has grown every year in our sample.

Figure C1 – Illustration of the Finnish Education System before and after the Polytechnic Reform 2002



Notes: Arrows indicate most important flows of students between schools. See also OECD (2003, p. 37) "Polytechnic Education in Finland". Paris: OECD; Ministry of Education (2005) "OECD thematic review of tertiary education: country background report for Finland", Publications of the Ministry of Education, Finland 2005:38; UNESCO (2007) "International Standard Classification of Education, ISCED 2007", http://www.uis.unesco.org/Library/Documents/isced97-en.pdf

Figure C2 – Age at Entry to Polytechnic Master's Programs in the Data

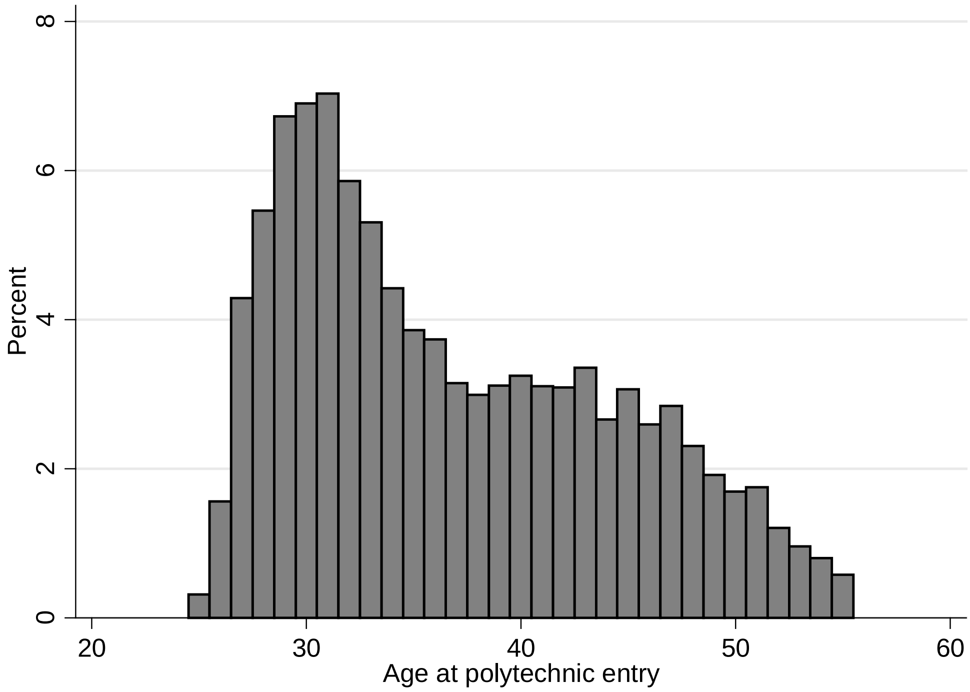
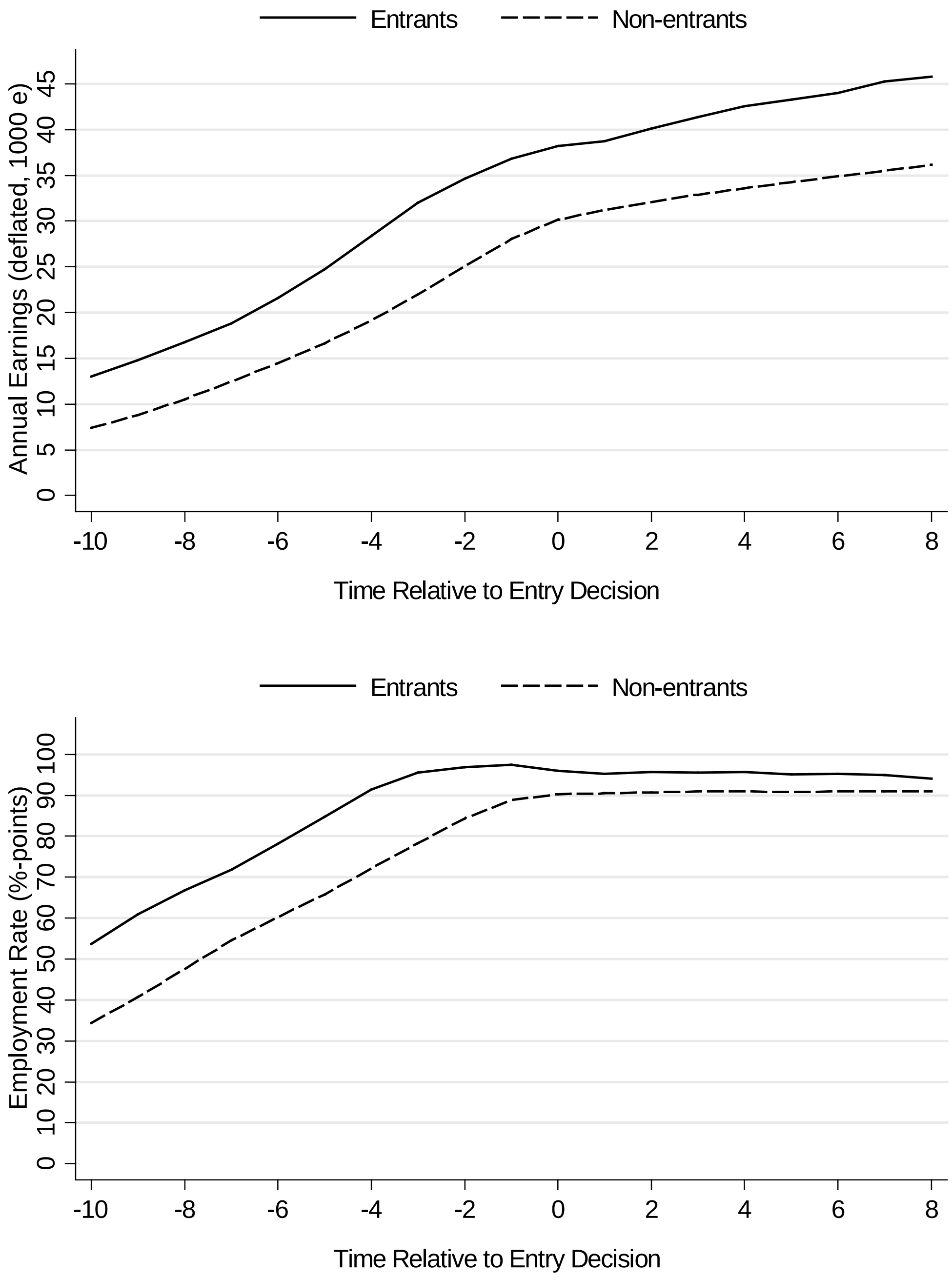


Figure C3 – Earning and Employment Development by Treatment Status



Notes: Number of entrants is 7,148 and number of non-entrants is 766,405 (no matching). Individuals are followed backwards until age 18.