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a within track comparison of workplace-based and school-based
vocational training in Hungary

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Abstract

Although apprenticeship training has been praised for its effectiveness in smoothing the school-to-work transition of non-college bound students, most studies rely on cross country or cross track comparisons. This study compares apprenticeship training students with non-apprentices *within* educational track using a rich database and a unique set of observable individual level characteristics as well as local labor market fixed effects to control for the potential selection bias. The results show that there are no significant differences in employment chances between apprentices and non-apprentices within just a year after graduation. Although, in small subsamples of the population, significant differences can be found, these are most likely due to unobserved heterogeneity. However, even if these observed differences are unbiased, they are more likely due to the superior screening of the larger firms rather than their superior training.

Keywords: apprenticeship training, employment, screening, school-to-work transition, panel data

JEL classification: J08, I21, I24, J24

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A Tanoncképzés Eredményessége

az iskolai és a vállalati szakmai gyakorlati képzés összevetése a szakiskolán belül

Horn Dániel

Összefoglaló

Bár a tanoncképzésről számos tanulmány megmutatta, hogy “kisimítja” a tanulók iskolából a munkaerőpiacra való átmenetét, a legtöbb empirikus tanulmány országok között vagy országon belül, de iskolatípusok között hasonlítja össze a tanoncokat és a nem tanoncokat. Ez a tanulmány adott iskolatípuson, a szakiskolán belül hasonlítja össze őket számos egyéni szintű jellemző és helyi munkaerőpiaci fix-hatások kontrolálásával. Az eredmények azt mutatják, hogy azon szakiskolás tanulók, akik a szakmai gyakorlatukat vállalatoknál végezték nem lesznek nagyobb valószínűséggel munkavállalók majdnem egy évvel a végzésük után, mint hasonló egyéni jellemzőkkel bíró nem-tanonc társaik. Bár a végzést követő hónapban látható szignifikáns különbség a tanoncok és a nem-tanoncok között egy almintán belül, ez a hatás leginkább meg nem figyelt egyéni jellemzőknek tulajdonítható. De ha feltételezzük, hogy a megfigyelt különbségek torzítatlanok, akkor is inkább a vállalati szelekciónak, semmint a képzés minőségének tulajdoníthatók.

Tárgyszavak: tanoncképzés, munkavállalás, szűrés, átmenet az iskolából a munkába, panel adatok

JEL kódok: J08, I21, I24, J24

1. INTRODUCTION¹

Measuring the effects of workplace-based vocational (apprenticeship) training relative to school-based vocational training on labor market outcomes has been a challenge. The problem “arises from the fact that the two vocational routes are rarely available to young people as direct alternatives in the first place. Vocational preparation at sectoral or occupational level typically depends within any one country exclusively on either apprenticeship or full-time schooling” (Ryan 1998, 309).

Many have tried to address this selection bias using selection equations (Bonnal, Mendes, and Sofer 2002; Bertschy, Cattaneo, and Wolter 2009; Meer 2007), or using pieces of information from different sources of exogenous variance (difference-in-difference method: Hanushek, Woessmann, and Zhang 2011; Noelke and Horn 2014; instrumental variable method: Parey 2009; Alet and Bonnal 2011).

This paper addresses the question of the effect of apprenticeship training on youth employment in a more straightforward manner. It compares workplace-based vocational training (apprenticeship) with school-based vocational training *within* educational track and industry using a rich and unique set of observable individual level characteristics to control for the potential selection bias.

In Hungary apprenticeship and non-apprenticeship students can be compared within the vocational training track and within industry. Students within this track receive the same general education, the same amount of practical training and the same exact qualification after successfully finishing school and taking the occupation specific exams. They only differ in their place of practical training: some gain experience while working for a firm as an apprentice while others gain knowledge on the same field within the school (school workshops or within the class).

The main aim of this paper is to test the assumed positive effects of workplace-based training on labor market entrance by using a new, individual panel database, the Hungarian Life Course Survey (HLCS). While the analyses below are not *per-se* causal, I try to convince the reader that controlling for a wide variety of observable individual characteristics, educational track, industry and local labor market effects tackles all important endogeneity concerns, and, thus, the remaining selection bias is minimal.

¹ Uncommon abbreviations in the text: Hungarian Life Course Survey (HLCS), National Assessment of Basic Competencies (NABC), vocational education and training (VET), special education needs (SEN)

The results of the analysis show that there is no significant difference in employment chance between apprentices and non-apprentices just a year after graduation. In fact, the only observable significant difference is between non-apprentices and apprentices in large firms, who organized their training individually. Looking at the detailed results below also sheds some light on the potential mechanism. The results suggest that the uncoordinated and decentralized Hungarian apprenticeship training is likely not to improve the skills of the students relative to that of the others (human capital argument), but motivated apprentices, as well as committed firms, might benefit from better matching procedure (screening argument).

2. PREVIOUS LITERATURE

Workplace-based training has long been praised for its effectiveness in preparing non-college bound youth for the labor market. In particular the “dual” vocational education and training systems at the secondary level, combining school-based vocational education with employer-provided, workplace-based training have sustained a positive track record in smoothing the school to work transition process, lowering the unemployment rate, and increasing the quality of work (Rosenbaum et al. 1990; Müller and Shavit 1998; Ryan 1998; Shavit and Müller 2000; Ryan 2001; Breen 2005; Wolbers 2007; Wolter and Ryan 2011; Piopiunik and Ryan 2012).

Several authors have directly compared apprenticeship training with full-time vocational training within country with similar results. van der Velden and Lodder (1995) and Plug and Groot (1998) look at the Dutch while Winkelmann (1996) studies the German education system and compare apprentices with similar students from alternative tracks. Both the Dutch and the German apprentices have a quicker transition to employment than their peers, but Plug and Groot (1998) hardly find any difference between the two tracks in terms of employment opportunities, earnings and earnings growth. Winkelmann (1996) also notes that once a student is employed, the stability of further employment is independent of her/his previous track.

While these conclusions are appealing, the potential selection bias in the estimates cannot be denied. In most countries, educational tracks are highly selective, and mostly on individual characteristics that can affect employment chances as well. More recent studies have thus increasingly started to address the selection bias in these cross-track comparisons. Bonnal, Mendes and Sofer (2002) and Bertschy, Cattaneo and Wolter (2009) try to model the selection into apprenticeship using French and Swiss data, respectively. Bonnal, Mendes and Sofer (2002) show that apprentices have a better chance of finding a job immediately

after graduation, which effect is mainly driven by the “stayers,” i.e. those that stay at the firm that provided the training. Bertschy, Cattaneo and Wolter (2009) find that the initial significant difference in employment in “adequate jobs,” which matches the graduate’s qualifications, between these groups disappears after they take selection into tracks into account.

Other papers address the selection bias by using other sources of exogenous variation. Noelke and Horn (2014) use the rapid change in apprenticeship training places in Hungary after the transition. Using the fact that the decrease in training places was different in the 20 different counties, they estimate a difference-in-difference model. They conclude that vocational graduates in counties with a larger share of apprenticeship training are less likely to be unemployed right after they enter the labor market, but this effect fades out some time after entry into the labor market. The authors find no differences in the quality of job acquired in the labor market.

Parey (2009) also uses a variation in the supply of apprenticeship places in local German labor markets as an exogenous predictor for individuals’ choice between firm-based apprenticeship training and fully school-based vocational program to identify the returns to apprenticeship training. He shows that apprenticeship training leads to substantially lower unemployment rates, which fade out over time.

Similarly to the above papers Alet and Bonnal (2011) uses variation in local apprenticeship share to instrument the probability of track choice. They argue that selection bias must be corrected since the naïve estimates point toward less favorable educational outcomes for the apprentices while the instrumented equations level out (or even reverse) the advantages.

In short, most of these studies argue that apprenticeship training is either beneficial in smoothing the school-to-work transition or at least it does not hurt apprentices relatively to other similar students. But how could apprenticeship help students? What are the potential mechanisms that drive the results?

The two distinct mechanisms according to Ryan (1998) are the “superior skill learning” of apprentices and the “associated institutional links” between the sides. The first refers to the human capital theory (cf. Becker 1994) where apprentices find their initial job more quickly because of their improved specific skills, which facilitate faster adoption to a new workplace, as well as higher productivity right from the start. “Specific skills” learnt at the workplace can either be specific to the firm or technologically general (cf. Acemoglu and Pischke 1998), meaning that although skills acquired at the firm are specific to a given technology, they can also be useful in other firms using the same technology.

The second mechanism is in line with the screening argument (cf. Stiglitz 1975; Spence 1973), which decreases the importance of skill-differences and presses that graduates with workplace-based training are already screened by employers and, thus, the risk of hiring someone with unfavorable characteristics is smaller than for graduates with school-based training. As Stevens argues “if firms face costs or difficulties in recruiting skilled labour, they can offset costs incurred in the training of apprentices against these” (Stevens 1994, 568; see also Acemoglu and Pischke 1999).

While both of these mechanisms offer distinct explanations on the smoother transition to work of apprentices, some of the above findings provide more support for the screening than the human capital argument. For instance the finding that in France apprentice “stayers” are more likely to find a job than “movers” (Bonnal, Mendes, and Sofer 2002; Mendes and Sofer 2004), or Euwals and Winkelmann’s (2004) observation that “stayers” in Germany are more likely to have longer first-job duration but not higher wages, support the screening more than the human capital argument. Winkelmann’s (1996) argument that once employed both “stayer” and “mover” apprentices and non-apprentices have similar job stability is also more in line with the screening mechanism and less with the human capital argument. The result that employment differences between apprentices and non-apprentices are likely to diminish quickly (Parey 2009; Noelke and Horn 2014) is also parallel with the screening argument.

Naturally, none of these results is conclusive, as none refutes the human capital mechanism perfectly.² Moreover, some other discoveries provide support for the human capital mechanism as well. For instance, the argument of Hanushek, Woessmann and Zhang (2011), who argue that the short-term benefits of vocational training might turn to losses in the long run supports the human capital mechanism. Employing a difference-in-difference approach that compares employment rates across different ages of people between countries of different vocational educational focus they show that the age-employment pattern is declining more for countries with vocational education relative to those with stronger general education, and it is the acutest in the three apprenticeship countries in their sample. In short, they provide support for the distinct employment effects of the skills set that people in vocationally oriented countries receive as opposed to the skills that people receive in countries with more general education.

This paper contributes to this literature by providing evidence from a unique institutional setting, where apprentices and non-apprentices can be directly compared. This comparison also allows for speculations about the potential mechanisms.

² e.g. „stayers” could be different from „movers” in their initial ability to learn, and hence those could stay at the training firm, who were able to benefit more from the training in terms of productivity.

3. THE HUNGARIAN VET SYSTEM

The Hungarian education system is unique in the sense that it allows for a within track comparison of apprentice and non-apprentice students even within the same occupation.

Most students choose between three tracks at the end of their 8th grade³: an academic track (*gimnázium*), and two vocational tracks. The vocational secondary track (*szakközépiskola*) mixes academic and vocational training and allows for tertiary entrance after graduation while the vocational training track (*szakiskola*) is non-college bound (see Figure A1 in the appendix). In 9th grade, a little more than 35% of the cohort is in academic secondary tracks. Another 60% of students go to vocational tracks: a large majority of them (over 40% of the full cohort) enter the vocational secondary, while around 20% enter the vocational training track. The remaining less than 5% of students are dropouts or those students with special educational needs (SEN), who cannot be integrated with the others and thus enrolled in special vocational training. While both the academic and the vocational secondary tracks offer general training for four years – and the vocational secondary offers pre-vocational training, with usually one or two optional years of vocational practical training after the school-leaving exam – the vocational training track offers only two years of general training⁴ with two additional years of practical training. This paper focuses on the 20%, who are enrolled in the vocational training track. This track is considered to be the lowest ranked in the hierarchy of tracks (but still above no-education).

All students in the vocational training track must choose a vocation and take on practical training within this vocation. It is the duty of the school to provide practical training for the student. The school can either organize the training within its boundaries (e.g. by hiring vocational teachers) or can “outsource” the training to a private firm. The student can also organize training for her/himself at a private firm. In all of these cases, a tripartite contract must be signed between the firm, the school and the student.

School-based training can either be organized at workshops that are physically outside the school but that are run by the school or in workshops or classrooms that are physically within the school. I will consider both of these as non-apprenticeship training. On the other hand, workplace-based training places can be organized by the school or the individual. School organized apprenticeship training is usually done in groups, but not necessarily. Their common feature is that the firm contacts the school first (or the school contacts the firm),

³ About 8% of each cohort enters the so called early-selective academic tracks after 4th or after 6th grade, thus students are already enrolled here at the end of their 8th grade.

⁴ This structure has changed after the law of 2011/CLXXXVII (on vocational training), in that students receive vocational training right from the first year, but this change has not affected the cohort of this study.

and then the candidate is selected. Irrespective of the location and the form of training all vocational training track students, within the same vocation, receive the same qualifications.

Naturally, selection into training places might not be random, but there is no central procedure that allocates students in one group or another. In fact, the organization of the system is overly school-based, with relatively few links to the labor market (Kis et al. 2008). The system has been one of the most-decentralized ones in the OECD (OECD 2004).

Firms also have (small) incentives to train students. All firms have to pay a contribution towards vocational training (a tax), which is 1,5% of the sum of the gross wages of the firm. Firm with less than 50 employees can use 60% while larger firms 33% of this amount to train their workers, including training apprentices. Apprenticeship students have to be paid at least 20% of the minimum wage while in training⁵, which amount is deductible from the contribution towards vocational training. Some further costs, such as the foregone earning of the trainers at the firm or some material costs can also be deducted.

So Hungary is an ideal place to test the pure effect of workplace-based training: not high, but existing incentives for firms to train, basically non-existent compensation for apprentices and two ideal groups to compare, both of which receive the same general training and same diplomas, but differ in their place of practical training. The only open question is how students are allocated between training places. After the introduction of the HLCS data, I will address this issue.

4. THE HLCS DATA

The Hungarian Life Course Survey (HLCS) is an individual panel survey conducted annually. The original sample of 10,022 respondents was chosen in 2006 from the population of 108,932 eighth-grade students with valid test scores from the National Assessment of Basic Competencies (NABC). The NABC measures the literacy and numeracy of all 6th, 8th and 10th grade students every year, starting from 2006 (OECD 2010). The NABC also contains a set of family background variables, such as parental education or employment status. The first HLCS survey wave was completed during the winter of the school-year 2006/7, and subsequent waves have been fielded on a yearly basis. Currently, there are six waves available with fairly large response rates. The annual sample attrition rate, on average, is only around 5% (see Table 1).

⁵ This amount is very small. The minimum wage in 2010 was 73500HUF that is approximately 260-270 EUR/month. Correspondingly, the average amount the apprenticeship students received in our data was 15361 HUF (~55 EUR) a month with a standard deviation of 5691 HUF.

Table 1

Basic statistics of the HLCS database

wave	School year	Date of the survey	Median school grade	Number of students (with oversampling SEN students)	Number of students (representative sub-sample)
1	2006/07	2006 fall	9	10022 (100%)*	7218 (100%)
2	2007/08	2007 fall	10	9300 (92,8%)	6716 (93%)
3	2008/09	2008 fall	11	8825 (88,1%)	6397 (88,6%)
4	2009/10	2009 fall	12	8333 (83,1%)	6071 (84,1%)
5	2010/11	2011 spring	13 (LM entry, post-secondary, vocational or tertiary)	7662 (76,4%)	5587 (77,4%)
6	2011/12	2012 spring	14 (LM entry, post-secondary, vocational or tertiary)	6974 (69,5%)	5111 (70,81%)

Note: LM = Labor Market

* The sample was selected from a population of 108932 students taking the NABC test, from whom 37027 students have indicated to be available for such a panel study. Of the initial 10000 sample 1484 were unsuccessful for various reasons (the most populous reasons are refuse to answer: 726, not available during the survey period: 143, moved: 131, four unsuccessful approaches: 143) and thus additional sample units from the given sampling unit was approached (more on this see Kézdi, Molnár, and Medgyesi 2007, in Hungarian)

The HLCS database contains detailed information on achievement (standardized literacy and numeracy scores in 8th grade from the NABC data as well as teacher given class marks in each year), ethnicity, school trajectory, family background – including parental education and employment –, and many other dimensions. The main blocks are family and financial situation, parents' work history, studies/school results, track change/dropout, labor market, and data on partner/child. Although students with special educational needs (SEN) are overrepresented in the data, propensity weights are used to control for the oversampling, as well as for the imminent sample attrition. The following strata were used during the data collection, and in estimating the weights: 1) three settlement types: the capital and big cities,

other cities, villages 2) 7 NUTS-2 regions⁶ 3) Reading literacy test scores (3 equal groups from the NABC 2006 reading literacy distribution plus the integrated SEN students).⁷

The most-important variables of interest in this paper are the school track, the apprenticeship status, and the labor market outcome. School track is defined as the student's school track in the 4th wave of the study, the year when the median student was finishing the last year of compulsory schooling. All students in the analysis were enrolled in the vocational training track in the 4th wave. Vocational training students could do their practical training (1) either within the school in class or workshop or (2) outside of the school in a school workshop or could go to a private firm, either (3) with the help of the school (usually in groups) or (4) organizing the training by themselves. I have merged the former two, and labeled them as school-based or non-apprenticeship training. I equated the latter two with apprenticeship training, although I will also use them separately in some specifications below. Everyone, who did workplace-based training in the 4th wave or in the 5th wave (the year after finishing compulsory education), is considered an apprentice, if they entered the labor market after that. Students, who were apprentices in the 4th wave but did another year of practical training as non-apprentices in the 5th wave are considered as non-apprentices.

The two last waves of the HLCS survey were fielded during the spring of 2011 and 2012. All questions used for the control variables refer to this time of the year. However, one set of retrospective questions were also asked about the labor market status of the respondents. In both of these waves, questions about the previous academic year were asked. That is, in 2012 students have reported their monthly labor market status between 2010 September and 2011 August while they reported their monthly status between 2009 September and 2010 August in 2011. I will use responses both from this retrospective question as well as from the main questionnaire referring to the time the survey was taken.

The labor market status could take on four different values: employed, unemployed, studying and other. The four possible options within the "other" category are disabled, on maternity-leave, caring for family and other reasons. Unfortunately, this category is rather scarce and very heterogeneous. It is likely that different reasons unrelated to apprenticeship training would make one to report being on maternity leave, caring for family or be disabled. The remaining respondents – the other of the other category – are probably also a heterogeneous group. Therefore, I have removed these respondents from the sample.⁸

⁶ The NUTS classification (Nomenclature of territorial units for statistics) is a hierarchical system for dividing up the economic territory of the EU.

⁷ Note that the same strata were used to recalculate the weights for the sample in this study, so that it represents the full cohort of vocational training students.

⁸ Note that including the „other/other“ respondent to the unemployed category (assuming that these are actually inactive) does not significantly change the results. Also note that I have dropped altogether 82 “other” responses of which 42 are the “other/other”, which is around 4% of the total responses.

The three types of labor market outcomes are employed, unemployed or studying. These are considered both in the 5th and in the 6th wave of the study depending on when students reported having practical training. If someone had practical training – either school- or workplace-based – only in the 4th wave, then outcomes from the 5th waves are used. However, if someone reported having practical training in the 5th wave as well, I used their 6th wave labor market status as the outcome variable.⁹ Table 2 contains the full set of (non-retrospective) outcomes for the 5th as well as for the 6th wave.

Table 2

Labor market outcomes in the 5th and 6th wave

	5th wave						6th wave					
	work	unempl.	study	other	missing	Total	work	unempl.	study	other	missing	Total
academic	70	54	1717	62	172	2075	187	95	1419	85	289	2075
%	3,37	2,6	82,75	2,99	8,29	100	9,01	4,58	68,39	4,1	13,93	100
voc.sec.	106	115	2037	62	158	2478	452	303	1219	161	343	2478
%	4,28	4,64	82,2	2,5	6,38	100	18,24	12,23	49,19	6,5	13,84	100
voc.tr.	148	189	958	62	114	1471	541	290	286	123	231	1471
%	10,06	12,85	65,13	4,21	7,75	100	36,78	19,71	19,44	8,36	15,7	100
spec.voc.tr.	23	34	191	12	26	286	60	45	108	25	48	286
%	8,04	11,89	66,78	4,2	9,09	100	20,98	15,73	37,76	8,74	16,78	100
missing	252	418	906	246	1890	3712	508	408	515	262	2019	3712
%	6,79	11,26	24,41	6,63	50,92	100	13,69	10,99	13,87	7,06	54,39	100
Total	599	810	5809	444	2360	10022	1748	1141	3547	656	2930	10022
%	5,98	8,08	57,96	4,43	23,55	100	17,44	11,38	35,39	6,55	29,24	100

Other variables that are used are the standardized test score (mean of literacy and numeracy) in 8th grade¹⁰, class mark averages (1- fail to 5- excellent) in 8th and in 12th grade, gender, SEN status, Roma ethnicity, grade repetition¹¹, parental education and occupation. All control variables are from the first wave of the study unless otherwise noted. From the initial 1471 vocational training students in the full sample, 1012 have values available for all

⁹ A binary variable for the two different types of students is included in all estimations (“no practical training in 5th wave”).

¹⁰ Note that these test scores cannot be used for the secondary level entrance, but are used to make schools accountable and to provide feedback for the teachers (see OECD 2010).

¹¹ I have used a proxy for grade repetition: whether the student was in the 12th grade in the 4th wave of the study, just as the median student.

the above variables.¹² The month of the survey is controlled in all estimations and is not shown. See Table 3 for descriptive statistics.

Table 3

Descriptive statistics for the sample of students in the analysis

Variable	obs.	mean	s.d.	min.	max.
apprentice	1012	0.65	0.48	0	1
math and reading test score (std.), 8th	1012	-0.56	0.67	-3.78	1.12
class mark average, 8th grade, imputed	1012	3.25	0.54	1	4.9
class mark average, 12th grade	1012	3.38	0.57	2	5
parents' ed.: primary or below	1012	0.23	0.42	0	1
parents' ed.: secondary or higher	1012	0.30	0.46	0	1
father employed, 4th wave	1012	0.55	0.50	0	1
father unemployed, 4th wave	1012	0.19	0.39	0	1
SEN student	1012	0.07	0.25	0	1
Roma	1012	0.07	0.26	0	1
12th grader in 4th wave	1012	0.81	0.40	0	1
female	1012	0.37	0.48	0	1
no practical training in 5th wave	1012	0.31	0.46	0	1

Most occupational qualifications available in Hungary are included in the National Training Register (Országos Képzési Jegyzék - OKJ). The HLCS also contains information on the type of the qualification for vocational graduates (see Table 4). The official list of qualifications contains 21 larger categories. I have grouped these into six broad categories (industries) in order to increase the number of cases within each category, but still facilitate relevant comparison between the groups (see Table A1. In the appendix).

I will use these six industry categories interacted with the 20 counties in most of the estimations below, assuming that industries within counties capture local labor markets well. Note that using these categories as fixed effects provides rather restrictive models with just over nine observations per cell on average and several empty cells. Nevertheless, I find it crucial to take the different characteristics of the local labor market into account: a well-developed industry might influence both the apprenticeship as well as the employment chances of the young. Unfortunately, due to the size of the dataset, more detailed division of labor markets cannot be taken into account.

¹² I have imputed little more than 3% of the values in the 8th grade class mark using all other individual variables in the regression, a dummy variable to control for the imputed values is included in all regressions and is not shown.

Table 4

Number and percentage of apprentices by industry

Industry	non-apprentice	apprentice	Total
social services	5	10	15
%	33.33	66.67	100
mechanics	91	127	218
%	41.74	58.26	100
industry	110	117	227
%	48.46	51.54	100
transport-environment	19	44	63
%	30.16	69.84	100
services	91	263	354
%	25.71	74.29	100
agriculture	73	62	135
%	54.07	45.93	100
Total	389	623	1,012
%	38.44	61.56	100

In some of the estimations below, I have further divided the *apprentice* variable. Larger firms might offer students a smoother transition to the labor market either through their higher training intensity (Winkelmann 1996; Euwals and Winkelmann 2004), more developed, more standardized training structure (Kotey and Folker 2007) or because of their higher level of commitment (Dustmann and Schönberg 2012). Hence looking at the effects of apprenticeship by firm size could highlight some interesting patterns, which could shed light on the potential mechanisms as well. The size of the training firm in the database can be either small (1 to 50 employed) or large (over 50 employed).¹³

Also students, who organize their training individually, might be different from their peers, who get their apprenticeship places through the school. Students, who organize training individually might be more motivated, or have stronger personal links to the local labor market. These are both unobservable characteristics that can also affect their ability to find a job after graduation.

Using firm size and type of organization of apprenticeship I have divided the *apprentice* variable into four categories: school-organized/small firm, school-organized/large firm, self-organized/small firm, self-organized/large firm (see table 5).

¹³ Unfortunately, the question about the size of the training firm have changed from wave 4 to 5, offering the 50 employed as the only common cut-off point between the small and the large firm. Thus no specification checks could be run.

Table 5

Number of apprentices by firm size and form of organization

		non-apprentice		apprentice		Total
		within school	outside school (workshops)	school-organized	self-organized	
non-apprentice		241	148	0	0	389
apprentice	small firm (<50)	0	0	264	170	434
	large firm (>50)	0	0	152	37	189
Total		241	148	416	207	1,012

5. SELECTION INTO APPRENTICESHIP

Before addressing the effectiveness of the apprenticeship training it is essential to understand, who chooses workplace-based and who chooses school-based training. There is only anecdotal evidence about the process of apprenticeship selection, and thus, endogeneity cannot be ruled out: students, who would more likely be employed at the end of the education, are also more likely to get an apprenticeship position. It is not unlikely that apprentices have different personal traits than non-apprentices, but it is also highly likely that the local labor market (the demand side), as well as the occupation of the trainee (the supply side), has an effect on the probability of employment. This potential selectivity is also true for the other two dimensions of apprenticeship training: firm size and form of organization. More motivated students or students with personal links to the local firms are more likely to get individually organized training places, and similar selectivity by firm size also cannot be ruled out.

Table 6 below shows the differences in the most-important individual characteristics between the five groups of students. Apparently there are no large differences between the groups of students, most of the differences are not significant, although there are a few that are significantly different (e.g.: self-organized apprentices in small firms tend to have relatively higher math and reading test scores compared to non-apprentices).

Note that these are only raw differences, and thus it might be that spatial and/or industry characteristic drive these differences: for instance, large firms are clustered around larger cities, which can easily impact the chances of students entering large firms, as well as correlate well with their family status or test scores through better schools. Taking the effects of the local labor market into account would be essential. However, multinomial logit model with a large number of fixed effects has not yet been fully developed (see Pforr 2011).

Table 6

Differences in the main individual characteristics between apprentices

			math and reading test score (std.), 8th		class mark average, 8th grade, imputed		parents' ed.: secondary or higher		12th grader in 4th wave		
			Freq.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
non- apprentice			389	-1.05	(0.03)	3.30	(0.03)	0.26	(0.02)	0.78	(0.02)
apprentice	school- organiz- ed	small firm	264	-0.96	(0.04)	3.35	(0.04)	0.32	(0.03)	0.79	(0.03)
		large firm	152	-0.99	(0.05)	3.27	(0.05)	0.26	(0.04)	0.84	(0.03)
	self- organiz- ed	small firm	170	-0.87	(0.05)	3.34	(0.04)	0.28	(0.03)	0.85	(0.03)
		large firm	37	-0.94	(0.10)	3.40	(0.10)	0.24	(0.07)	0.70	(0.08)

Thus, I use the binomial non-apprentice/apprentice division and rely on linear probability models to assess the strength of association between personal traits and training provisions. Additional advantage of the linear probability models, besides handling large number of fixed effects, is that its fit (R-squared) can be interpreted more straightforwardly than the fit of the non-linear models (e.g. BIC or AIC), moreover within groups weights cannot be used in fixed-effect logit models. Table 7 below shows three distinct estimations. Model (1) is without the local labor market fixed effects, model (2) includes these fixed effects while model (3) is without the individual controls.

Apparently, only a few individual characteristic associate significantly with the provision of apprenticeship training. Students with inactive fathers are more likely to get an apprentice position, and girls are also more likely to do workplace-based training. Individual variables can explain 4-5% of the total variance. When local labor market effects are controlled, the power of the model increases considerably: more than 23% of the variance is explained. Also, all individual coefficients have lost their significance, which suggests that the local labor market explains most of the allocation of apprenticeship places. This argument is also underlined by model (3), where the adjusted R-squared drops only slightly to 22%. Looking at the AIC and BIC values also underline the superiority of the fixed-effect model, but they are not very straightforward on the usefulness of the individual characteristics.

From these results I conclude that while sorting into apprenticeship places on individual characteristics cannot be ruled out, it is likely that the selection is minimal, and also that difference between local labor markets in apprenticeship training allocation is more important.

Table 7

Selection into apprenticeship – linear probability models

	(1)	(2)	(3)
class mark average, 8th grade, imputed	-0.0929 (0.0673)	-0.0885 (0.0691)	
jegy_atlag_d	-0.115 (0.164)	-0.189 (0.125)	
class mark average, 12th grade	0.0597 (0.0579)	0.0525 (0.0647)	
math and reading test score (std.), 8th grade	-0.0289 (0.0567)	0.0325 (0.0460)	
parents' ed.: primary or below	-0.0465 (0.0854)	0.0152 (0.0788)	
parents' ed.: secondary or higher	0.0361 (0.0628)	-0.0407 (0.0532)	
father employed, 4th wave	-0.164** (0.0674)	-0.0653 (0.0531)	
father unemployed, 4th wave	-0.118* (0.0639)	-0.0816 (0.0614)	
SEN student	-0.0178 (0.0563)	-0.00171 (0.0530)	
Roma	-0.0731 (0.0839)	-0.134 (0.101)	
12th grader in 4th wave	-0.0467 (0.0669)	-0.00479 (0.0547)	
female	0.144** (0.0674)	-0.0311 (0.0670)	
no practical training in 5th wave	-0.0145 (0.0600)	-0.0379 (0.0522)	
Constant	0.829*** (0.233)	0.819*** (0.208)	0.647*** (0)
Observations	1,012	1,012	1,012
County*Indusrty FE	-	+	+
indiv. vars.	+	+	-
R-squared	0.062	0.297	0.271
R-squared adjusted	0.046	0.236	0.222
AIC	1346.596	1052.299	1057.474
BIC	1430.231	1131.014	1057.474

Robust clustered standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

6. DOES APPRENTICESHIP TRAINING INCREASE EMPLOYMENT CHANCES?

The ideal model to test this question would be a fixed-effect multinomial logit model that could take all outcomes, as well as the effects of local labor markets into account. Due to econometric problems with such models (see Pforr 2011), I have opted for a simpler estimation strategy. I transformed the original three category outcome (employed, unemployed, study) into two binary variables: *employment* (1- employed, 0-unemployed or study) and *studying* (1- study, 0-employed or unemployed). Note that *studying* is exactly opposite to “labor market entrance” as other outcomes (scarce in the sample) are excluded from the estimation.

Table 8

Effects of apprenticeship training - multinomial probit model, probability of being employed or studying wrt. being unemployed

	employed	study
apprentice	0.062 (0.068)	-0.048 (0.069)
class mark average, 8th grade, imputed	-0.001 (0.066)	0.056 (0.063)
class mark average, 12th grade	0.000 (0.056)	-0.003 (0.058)
math and reading test score (std.), 8th grade	-0.105** (0.044)	0.125** (0.057)
parents' ed.: primary or below	-0.062 (0.060)	-0.263*** (0.078)
parents' ed.: secondary or higher	0.080 (0.061)	-0.081 (0.068)
father employed, 4th wave	0.083 (0.060)	-0.073 (0.063)
father unemployed, 4th wave	0.008 (0.064)	-0.022 (0.084)
SEN student	-0.009 (0.054)	-0.003 (0.056)
Roma	-0.063 (0.081)	0.164 (0.104)
12th grader in 4th wave	0.140*** (0.049)	-0.141** (0.062)
female	-0.261*** (0.066)	0.091 (0.067)
No practical training in 5 th wave	-0.086 (0.054)	0.013 (0.059)
<i>N</i>	1,012	1,012

Robust clustered standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Running linear probability models on these two binary variables should provide very similar results to multinomial models. Table 8 shows the marginal effects at the mean estimated from a multinomial probit model, without the industry, county or labor market fixed effects (county*industry). Table 9 shows the coefficients (the average marginal effects) from linear probability models, with and without the fixed effects. Models 2 and 8 in table 9

correspond to the multinomial probit estimates in table 8. Apparently both models provide very similar point estimates: 6,2% and 6,5% on employment and -4,8% and -5% on studying, respectively.

Table 9

Effects of apprenticeship training – linear probability models						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	employment					
apprentice	0.0268 (0.0738)	0.0654 (0.0639)	0.0198 (0.0726)	0.0815 (0.0706)	0.0464 (0.0630)	0.0348 (0.0748)
Constant	0.395*** (0.0787)	0.250 (0.234)	0.398*** (0.0786)	-0.0566 (0.0751)	0.0634 (0.212)	0.322 (0.211)
Observations	1,012	1,012	1,012	1,012	1,012	1,012
R-squared	0.011	0.128	0.089	0.093	0.227	0.286
Industry FE	-	-	-	+	+	
County FE	-	-	+	-	+	
indiv. chars.	-	+	-	-	+	+
County * Industry FE						+
	(7)	(8)	(9)	(10)	(11)	(12)
	studying					
apprentice	-0.0369 (0.0865)	-0.0504 (0.0661)	- (0.0645)	-0.0478 (0.0669)	- (0.0506)	-0.0100 (0.0620)
Constant	0.323*** (0.0838)	0.468* (0.262)	0.273*** (0.0694)	0.122 (0.0976)	0.176 (0.209)	0.471** (0.192)
Observations	1,012	1,012	1,012	1,012	1,012	1,012
R-squared	0.014	0.108	0.089	0.096	0.223	0.301
Industry FE	-	-	-	+	+	
County FE	-	-	+	-	+	
indiv. chars.	-	+	-	-	+	+
County * Industry FE						+
Robust clustered standard errors in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

Table 9 also shows the separate effects of the individual characteristics, county and industry fixed effects on the effect of apprenticeship. While there are marginal changes in the point estimates, the full models (models 6 and 12) do not differ substantially from the base models (models 1 and 7), which show the raw differences in employment/study probability between apprentices and non-apprentices.

All of these results show that there are no significant differences between apprentices and non-apprentices in employment probabilities or in their probability of entering the labor market (i.e. not studying) less than a year after finishing vocational training.

Figure 1a below depicts the probability of employment of apprentices and non-apprentices using the retrospective variables. The estimated coefficients are from models identical to model 6 in table 9, with outcome variables from different months (the coefficients in May are exactly the ones from table 9 model 6). Figure 1b depicts the marginal effect of apprenticeship training, i.e. the difference between the probability of employment between similar apprentices and non-apprentices. There are no differences in employment probabilities between similar apprentices and non-apprentices either during the school-year or even right after that; although slightly larger increase in employment probability is apparent for apprentices one month after the end of school-year.

Figure 1a

Probability employment for apprentices and non-apprentices

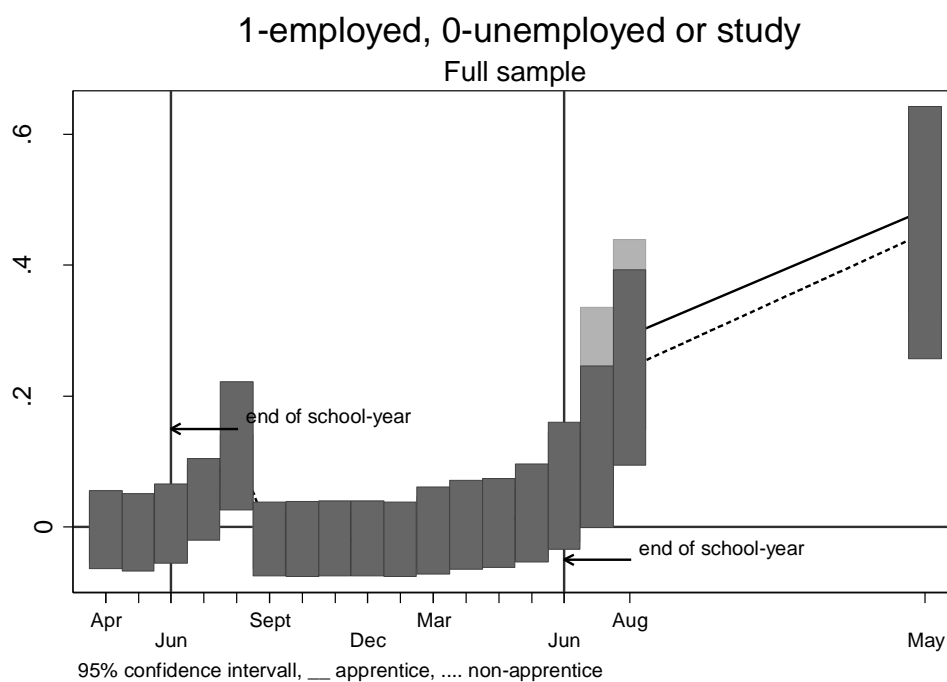
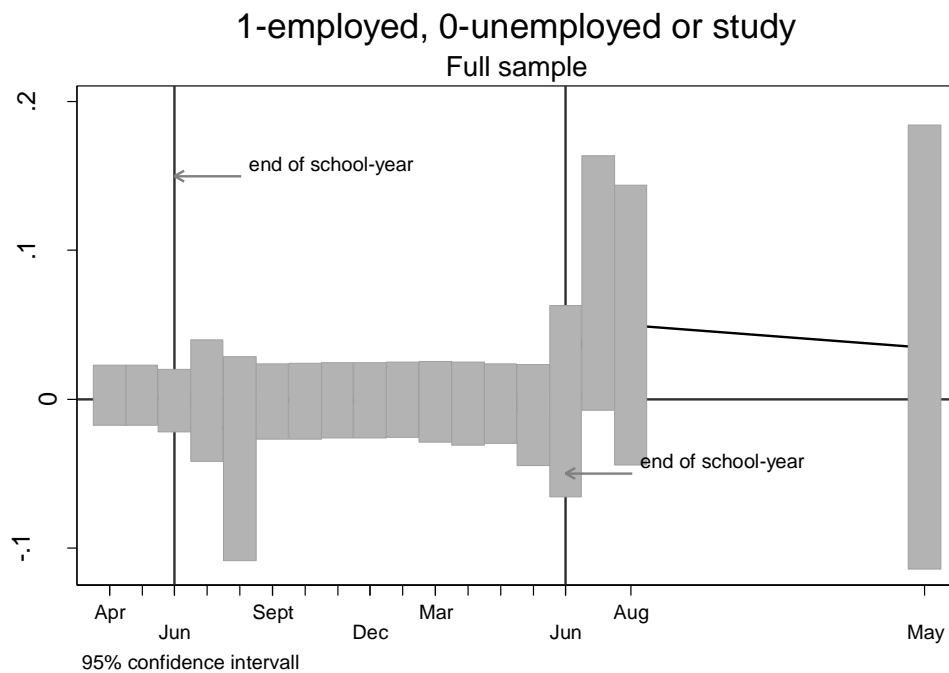


Figure 1b

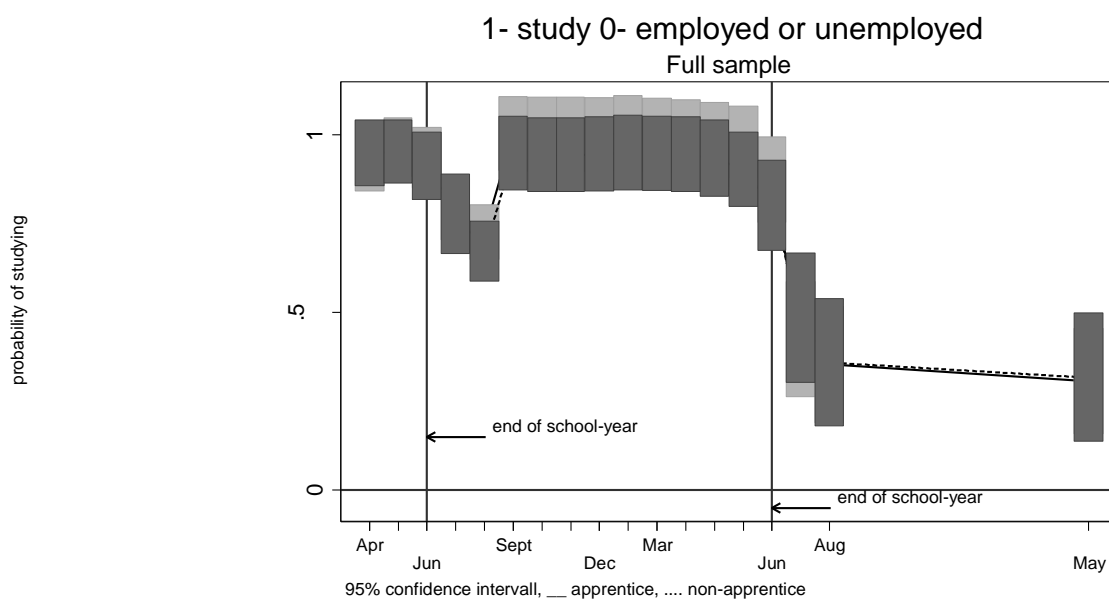
Marginal effect of apprenticeship training on the probability of employment



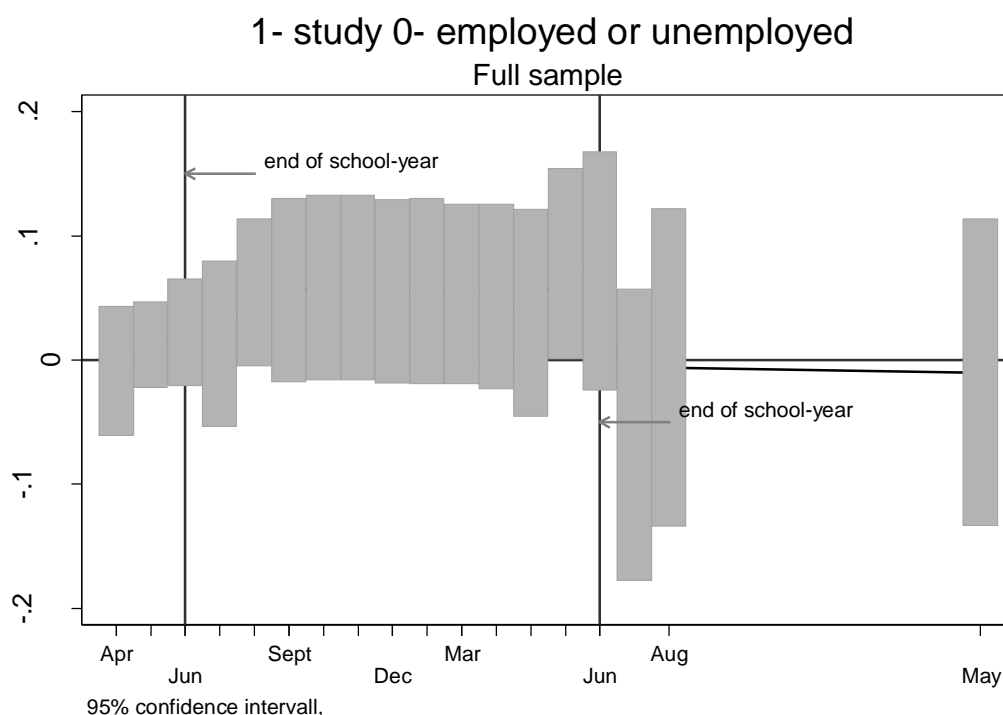
The same conclusion can be drawn on the probability of studying: there are no significant differences between the average apprentice and non-apprentice either one year after finishing the vocational training school or right after that.

Figure 2a

Probability studying for apprentices and non-apprentices



Marginal effect of apprenticeship training on the probability of studying



DIFFERENCES BY FIRM SIZE AND ORGANIZATION OF SCHOOLING

As elaborated above larger firms might be more effective in smoothing the school-to-work transition of apprentices than smaller ones. Also, students organizing training individually might be different from the others as they might differ in their unobserved characteristics.

Table 10 below shows the effect of the different firm size and the different types of organization of apprenticeship training as well as their interaction. Apparently neither the size of the firm nor the type of organization matters one year after graduation. However, it seems that apprentices of large firms, who have organized their own places, have much lower chance of studying a year after graduation than the other students. Note that this also means that these students are more likely to be in the labor market either as employed or as unemployed. While the reasons for this difference are not obvious, most likely there are some unobserved differences between these self-organized apprentices at large firms and the others. It might be that they are more committed towards their own occupation – and hence they individually applied to a large firm – and after gaining the necessary qualification they

stay within a given industry and do not pursue additional training even if they get unemployed.¹⁴

Table 10

Effects of different types of apprenticeship training – linear probability models

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	employment			studying		
apprentice: school-organized	0.0106 (0.0727)			0.00455 (0.0675)		
apprentice: self-organized	0.0793 (0.0901)			-0.0369 (0.0756)		
appr.: small firm (<50)		0.0391 (0.0721)			0.00352 (0.0624)	
appr.: large firm (>50)		0.0250 (0.102)			-0.0411 (0.0835)	
small firm/sch. org.			0.00847 (0.0730)			0.00205 (0.0661)
large firm/sch. org.			0.0164 (0.0890)			0.0256 (0.0925)
small firm/self org.			0.0850 (0.0805)			0.0186 (0.0804)
large firm/self org.			0.0582 (0.194)			-0.245*** (0.0866)
Constant	0.317 (0.211)	0.323 (0.211)	0.314 (0.212)	0.474** (0.193)	0.475** (0.192)	0.459** (0.184)
Observations	1,012	1,012	1,012	1,012	1,012	1,012
R-squared	0.288	0.286	0.288	0.302	0.302	0.310
County * Industry FE	+	+	+	+	+	+
indiv. chars.	+	+	+	+	+	+

Robust clustered standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figures 3a and 3b depicts the change in employment probabilities and the marginal effects of apprenticeship training by the size of the firm and the type of organization throughout the year. Unsurprisingly both apprentices and non-apprentices have a large increase in their employment chances right after graduating from school. But while students in school-organized apprenticeship places find jobs just as quickly as non-apprentices, self-organized students have a slightly smoother transition to the labor market. While on average 10-15% of non-apprentices and apprentices in school-organized places work regularly one month after graduation, this number is around 26% for the self-organized apprentices at small firms and a much higher 56% for apprentices at large firms. Although these numbers

¹⁴ Note that although this group of students is less populous (N=37), they are relatively well spread across industries as well as across counties.

converge through time, apparently self-organized apprentices at large firms enjoy a much smoother transition to the labor market than the others.

There is a couple of possible explanations of this marked difference between self-organized apprentices at large firms and the others. It might be that larger firms are more committed to training apprentices than smaller firms. Larger firms tend to plan for the long run and assume that their long-term productivity relies on the quality of the local labor market, and hence put more resources in apprenticeship training than small firms. This commitment is less likely in the case of small firms since their relative training costs might be much larger than that of the larger firms, and they can also easily free-ride on local large firms.

This speculation, however, is contradicted by the fact that there are no differences between non-apprentices and school-organized apprentices in larger firms. Although it is possible that large firms that select apprentices individually also use different training strategy than those, who directly contact the schools for apprentice supply, it is much more likely that it is not the training strategy, but the selection mechanism that differ between these large firms. That is; the most-likely explanation is that there is still some unobserved heterogeneity between self-organized apprentices at large firms and the others. It is reasonable to assume that the most motivated and committed students apply individually to large firms, and this unobserved individual characteristic has an impact on their labor market outcome as well. This is also underlined by the fact, that self-organized students are more likely to get a job right after finishing school even in small firms, although this difference quickly disappears.

While the most-likely reason for the observed significant effects is biased results due to omitted variables, one might also speculate about other potential reasons. Assuming that the observed effects are not biased they point towards the screening, rather than the human capital explanation. The differences across the school- and self-organized dimension are more likely caused by the different screening of the firms rather than their different training mechanisms. Firms that select students individually can screen them first, and after the training they can keep the better students. Probably larger firms have more advanced screening mechanisms than smaller firms, and also they tend to use less of the other channels – such as personal networks – for recruitment than the small firms. This would explain differences across the firm size. Nevertheless these are only speculations about the mechanisms and not proof.

Figure 3a

Probability employment for apprentices and non-apprentices by firm size and type of organization

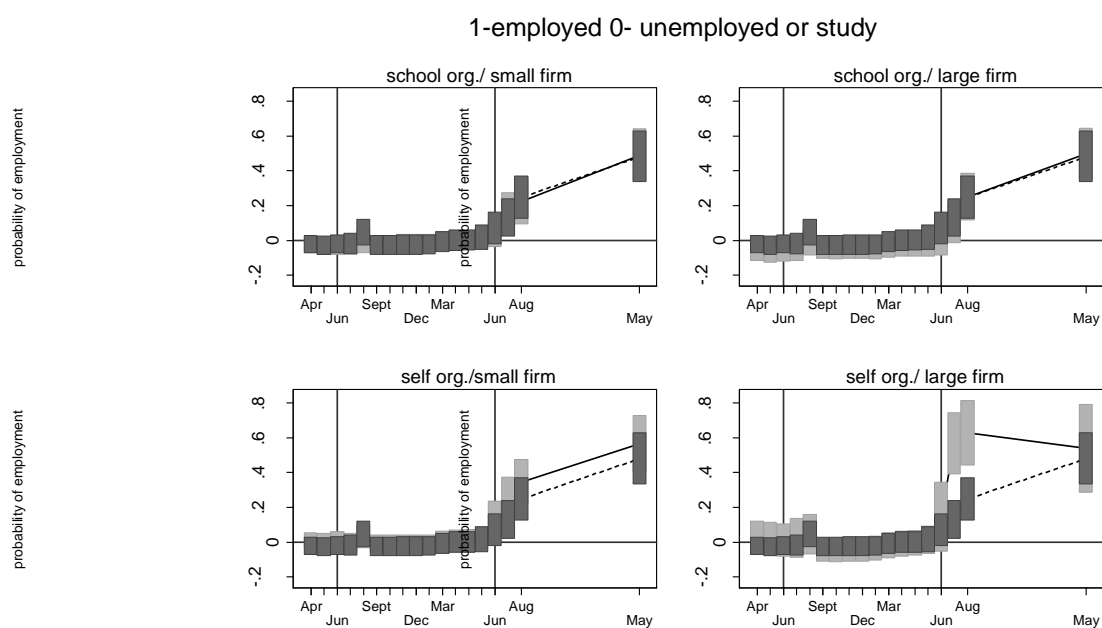


Figure 3b

Marginal effect of apprenticeship training on the probability of employment by firm size and type of organization

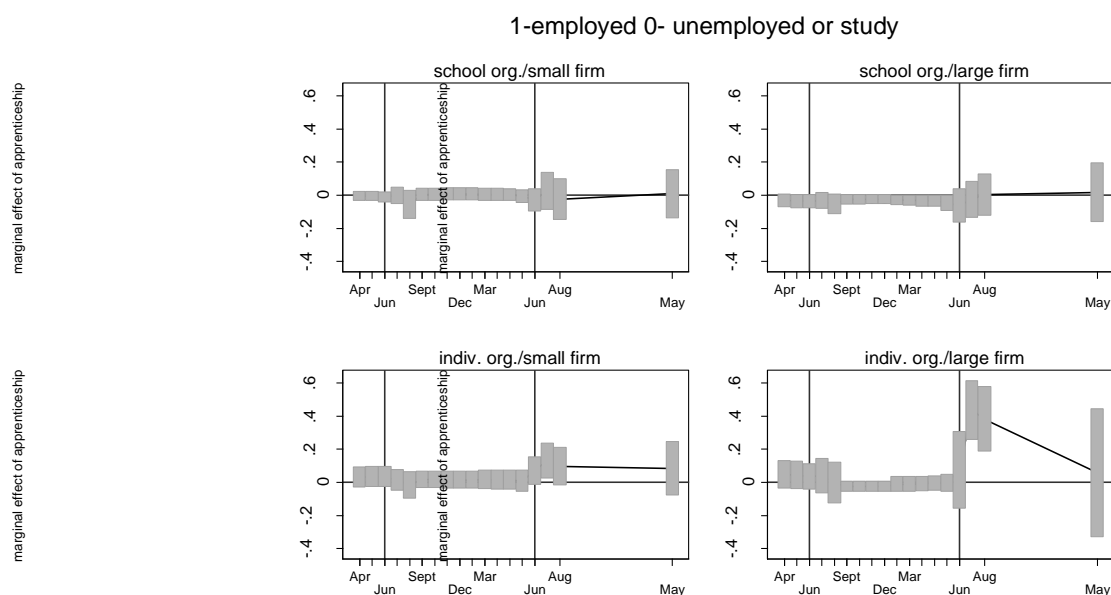


Figure 4a

Probability studying for apprentices and non-apprentices by firm size and type of organization

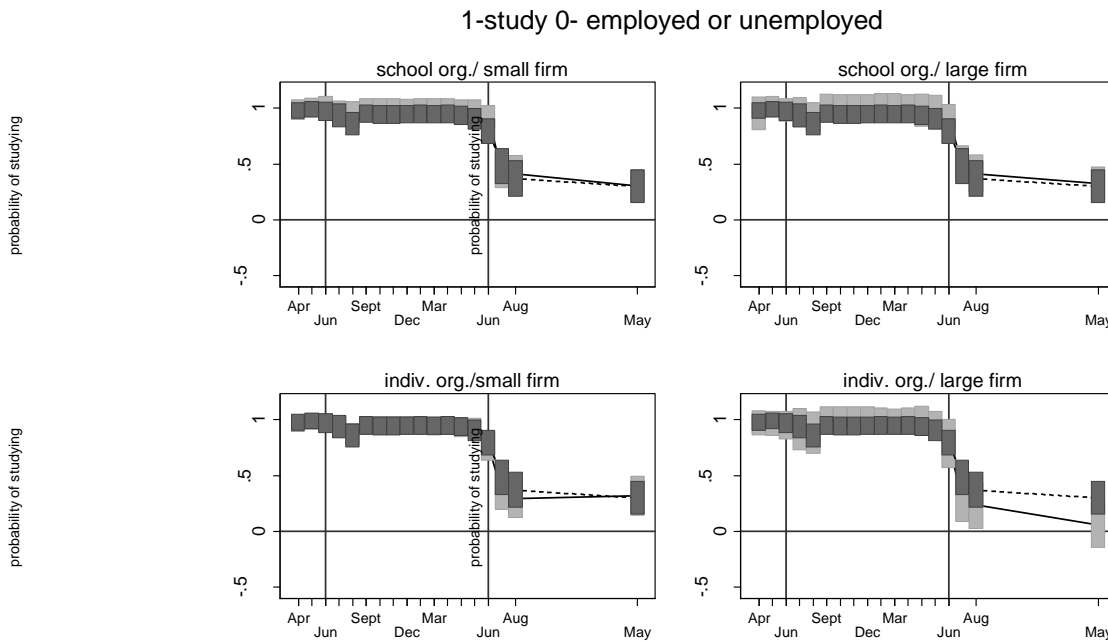
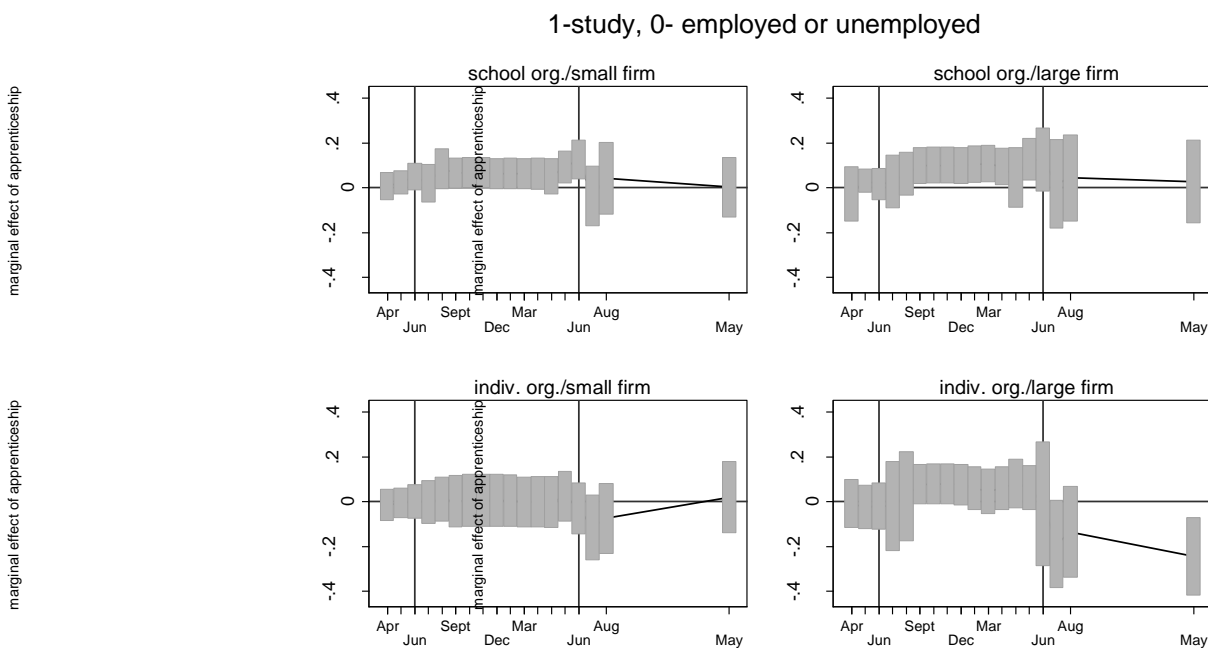


Figure 4b

Marginal effect of apprenticeship training on the probability of studying by firm size and type of organization



The above results, however, highlighted that apprenticeship training is not as influential in a decentralized, uncoordinated system as it is claimed to be in the established dual systems of Europe. It might be that this is due to the systemic failure of the Hungarian system to train or screen apprentices properly, but it might also be that previous cross-country or cross-track studies just failed to control for the most-important individual and labor market characteristics.

7. CONCLUSION

Previous research tends to argue that apprenticeship training in dual systems is beneficial especially in smoothing the school-to-work transition of apprentices (e.g. Ryan 1998; Wolter and Ryan 2011; Piopiunik and Ryan 2012). While this paper does not refute the advantages of workplace-based vocational training entirely, it puts a solid question mark on its significance, at least in an uncoordinated and decentralized vocational education context.

This paper addresses the question of the effect of apprenticeship training on youth employment in a rather straightforward manner. It compares apprenticeship training students with non-apprentices *within* educational track and industry using a rich and unique set of observable individual characteristics to control for the potential selection bias. The results of the analysis show that there is no significant difference in employment chance or in studying between the average apprentice and non-apprentice just a year after graduation. While there is a small, but significant marginal effect of apprenticeship training on employment chances right after graduation, this is clearly driven by apprentices in large firms, who organize their training individually. These students tend to find a job more quickly than non-apprentices or apprentices at small firms or large firms with school-organized places. This difference, however, disappears very quickly. The results also show that these apprentices at large firms, who organized their own places are more likely to refrain from further studying. These results suggest that the differences are probably still driven by unobserved individual characteristics, such as motivation or commitment. If so, apprenticeship training has no effect on labor market outcomes, when important individual characteristics and industry and labor market effects are controlled. But even if there is no omitted variable in the analysis an uncoordinated and decentralized apprenticeship training system, such as the Hungarian, is likely not to improve the skills of the students relative to that of the others. The differences are easier explained by an advanced screening process where motivated and committed apprentices, as well as their training firms, might benefit from better matching procedure in smoothing the school-to-work transition.

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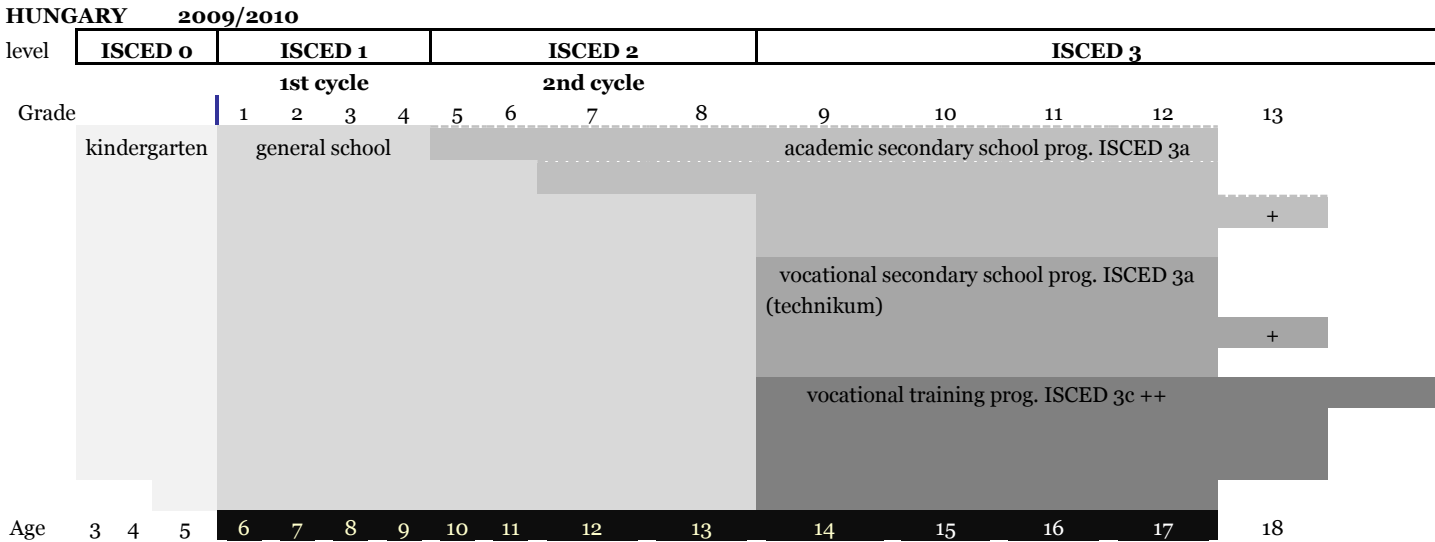
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APPENDIX

Figure A.1

The Hungarian compulsory education system



compulsory education until the age of 18 applies for the 1st graders in 1998 and later (previously and from September 2012: until the age of 16)

vocational secondary school programs curriculum includes vocational subjects and many students progress to PS voc to get a VQ

+ : some schools offer an extra grade teaching a foreign language before secondary school educ. (i.e. between grade 8 and 9)

++: some programs are also available for elementary school drop-outs

ISCED	English	national language	share
0	kindergarten	óvoda	100%
1,2a	general school	általános iskola	
3a	academic secondary school prog.	gimnázium	
3a	vocational secondary school prog.	szakközépiskola	
3c	vocational training prog.	szakiskola	

Table A1

Old and new categories of the national training register (OKJ)

New categories (industries)	Original categories in the national training register
Social Services	Health
	Social services
	Education
	Art, culture, communication
Mechanics	Engineering
	Electrical-engineering, electronics
	Informatics
Industry	Chemical industry
	Architecture
	Light industry
	Wood industry
	Printing industry
Transportation-environment	Transportation
	Environment and water-management
Services	Business and economics
	Management
	Trade, marketing and administration
	Catering, tourism
	Other Services
Agriculture	Agriculture
	Food industry