SCHOOL-BASED VOCATIONAL OR WORKPLACE-BASED APPRENTICE TRAINING?

Evidence on the school-to-work transition of Hungarian apprentices

DANIEL HORN
Max Weber fellow
EUI, Florence, Italy
Daniel.Horn@eui.eu

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(around 11,000 words)

Abstract

Workplace-based training has been praised for its effectiveness in smoothing the school to work transition. Apprentices have been shown to have lower initial unemployment probabilities as compared to other secondary graduates. There are but a handful of studies that could convincingly show that the effect of apprentice training on labor market outcomes is causal. This study provides additional support for the argument that workplace-based practical training increases initial employment probabilities. Using a unique individual panel database which includes, among others, extensive controls for individual skills, school attainment and parental background, it is shown that Hungarian students in the lowest, non-college bound vocational training track have about a 10% higher probability to be employed after leaving school as opposed to graduates of the same track, who had done their practical training within the school. This effect seems to be stable across industries. The data also shows that apprentices, when employed, earn the same amount of money, but more likely to receive long-term contracts compared to non-apprentices. Moreover, apprentices, who move to another industry, are less likely to receive long-term contracts compared to "stayers" but more likely to receive long term contracts compared to non-apprentices. These results suggests that it is not the increased specific skills of apprentices, but rather the signaling effect of apprenticeship training that smoothes the school to work transition.

Introduction

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 (VET) systems at the secondary level combining school-based vocational education with employer-provided, workplace-based (apprentice) training have sustained a positive track record in smoothing the school to work transition process, lowering unemployment rate and increasing the quality of work (Rosenbaum et al. 1990; Müller and Shavit 1998; Shavit and Müller 2000; Ryan 2001; Breen 2005; Wolbers 2007; Wolter and Ryan 2011; Noelke and Horn 2011; Piopiunik and Ryan 2012). Nevertheless, existing empirical research provides little information about the causal mechanisms that make the mixed school and workplace-based education effective. In particular, the mechanisms that explain why apprentices find their first job quicker than non-apprentices are empirically not well tested.

This paper improves existing literature in two ways. It adds empirical support on the positive causal link between workplace-based training and early labor market outcomes, and provides tests on the potential reasons why apprenticeship training causes smoother school to work transition. Note that this study looks at the supply side of the market rather than the demand side. The question is thus not why firms provide apprentice training, but whether apprentices are better off, and if yes, why?

Causal relation

There are at least four problems in the way of determining the causal effects of apprenticeship training on the individual level labor market outcomes (see Wolter and Ryan 2011). 1) It is hard to implement the counterfactual. What are the foregone choices for students entering apprenticeship training? Which group of students/workers would be the "control group"? While this question is inherently an empirical one, many previous studies could consider differences between different school tracks only (e.g. Breen 2005; Wolbers 2007; Rosenbaum et al. 1990; Müller and Shavit 1998; Shavit and Müller 2000). This comparison, however, is problematic, since 2) the allocation of young people to upper-secondary programs is not random (see e.g. Bertschy, Cattaneo, and Wolter 2009), which increases the probability of omitted variable bias, and thus makes estimations unreliable. The problem is not only that students are selected or self-selected into the different programs, but also that curricular or quality differences between school-programs make it hard to establish, whether the different types of schools or the differences in school-based vs. workplace-based training drives the results. Moreover, 3) the effects of apprentice training could differ between occupations. Some occupations might be learnt in school, while practical skills – acquired in firms – might be essential in another. Also, since the distribution of training provision varies between occupations, the lack of such information can easily bias the results. And finally 4) the usual outcome of unemployment or income could be argued not to cover all possible fields where apprenticeship might benefit/harm the students.

The first aim of this paper is to eliminate most of the above concerns when testing the effects of workplace-based training on labor market entrance using a new panel database, the Hungarian Life Course Survey (HLCS). The study compares two groups of students within one secondary level program (track). It is possible to look at the vocational training track, and compare those who have taken workplace-based training (apprentices) with those who were enrolled only in school-based training. Due to the institutional setup of the Hungarian VET system (see below) non-college bound students, who enter the "lowest" vocational training track could either do their compulsory practical training at firms or within the school. Hence the "treatment" and the "control" groups within the system are quite obvious: both groups have received the same general training (first two years in the vocational training program) and they might even go to the same school; the only difference is the place where practical training takes place. Although the allocation of students between training places is most likely not random, the HLCS offers an exceptionally wide variety of controls, which reduces the omitted variable bias concern. Moreover, the HLCS is a panel database which rules out the problem of inverse causality. The database also includes information on the types of qualification that students have acquired, which allows for an industry (proxy for occupation) control on the individual level. Finally the database is rich enough to test the effect of apprentice training on several labor market outcomes including, besides the usual unemployment probability, the net earning, the length of contract and post-secondary training.

Hungary is also a good country to study the effects of apprenticeship training. The Hungarian VET is not a dual-system per se. In fact, the system is very much 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). So if having practice at a private firm is indeed beneficial, Hungarian apprentices can really profit from this experience. Also, the outcomes of the Hungarian VET system are around the OECD average. The youth unemployment relative to adults ratio, the "neither employed nor in education or training" ratio, and the share of upper-secondary vocational students are all around the middle (Piopiunik and Ryan 2012), which suggests that Hungarian VET is most likely not an outlier and that the conclusions might be generalizable to other VET systems as well.

The second aim of the paper is to provide some empirical results on the potential reasons of decreased unemployment of apprentices. Why do students benefit from apprentice training? To put it simply, there are two main lines of argument (Acemoglu and Pischke 1998; Plug and Groot 1998; Wolter and Ryan 2011). The first is a human capital argument: apprentices find their initial job faster due to their improved skills,[1] which facilitates faster adoption to the new workplace as well as higher productivity right from the start. The second is a screening argument: 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. Or similarly, training firms select their future employees already when they hire apprentices; that is they equate this period of VET training with the usual probation period.

While both arguments predict lower initial level of unemployment for apprentices, there are differences in the prediction of other outcomes. The human capital argument predicts higher income for the increased productivity of apprentices, while a pure screening argument does not. On the other hand the screening argument puts forward a higher ratio of long-term contracts for apprentices – cf. apprenticeship as the probation period – but the human capital argument does not. Moreover, the screening argument would predict that apprentices, who move to a different firm after the training period is over, should be in a similar position to non-apprentices. The human capital argument on the other hand would predict that these "movers" have a higher chance of being employed.

Note that there are limitations of apprenticeship (see Ryan 2011). The benefits of apprenticeship might differ not only across occupations but also across students. Some might prefer the theoretical while others the practical approach, and we know little about the distribution of these groups. Also employers might utilize apprentices as "cheap labor", i.e. consider them as a source and not as an investment (Ryan 2011; Mohrenweiser and Zwick 2009; Wolter and Ryan 2011), which suggests that apprentices might not profit from

[1] Skills can either be general, or technologically general (cf. Acemoglu and Pischke 1998), meaning that although skills acquired at the firm are technologically specific, but can be useful in other firms using the same technology.

workplace-based training in terms of human capital. Moreover, it is very hard to strike the right balance between academic and practical training, or between general and specific skills. The over-abundance of either – in case of VET – might be considered harmful either in the short run (no specific skills) or in the long run (no general skills). In relation to this, the immediate benefits of apprentice training – such as the smoother school to work transition – might be counterbalanced by long run disadvantages (Plug and Groot 1998; Ryan 2001). Hence, it is not at all obvious that apprenticeship is indeed beneficial for all, even in the short run.

Previous research

There are but a handful of empirical studies that offer analysis on the causal effects of apprenticeship training on individual level labor market outcomes (see Wolter and Ryan 2011). These analyses almost exclusively predict that apprentices benefit from workplace-based training in that their initial employment probability is higher, but their methods, additional tests and conclusions differ.

Bonnal et al. (2002) show for France that apprentices have a better chance of finding a job immediately after graduation, but this effect is mainly driven by the “stayers”, i.e. those that stay at the firm that provided the training. Female apprentice “movers” have the same (or lower) employment probability than non-apprentice vocational students, while male “movers” have also lower employment probability than “stayers”, but similar or higher than non-apprentices. The authors argue that this finding can be due to three distinct reasons, among which they cannot discriminate: a) apprentices might lack the general human capital, as opposed to non-apprentice VET students, and thus finding job at a new firm is harder/not-easier; b) “movers” might be negatively selected, as those, who are not hired by the training firm might have some unobserved negative trait; and similarly c) there might be a negative signaling effect associated with moving to another firm, even if "movers" are not different from "stayers" in other respects. Nevertheless, all these considerations point more towards the signaling model than the human capital model.

Other studies that look at the causal link worry less about the reasons of increased employment chance. Bertschy, Cattaneo and Wolter (2009) also find that full-time vocational students are less likely to finish education successfully, as opposed to apprentices, and hence less likely to find an adequate job 1 ¾ years after the modal student finished education. But their focus is on another important point in this topic. Looking at the Swiss training system, they emphasize that self-selection into educational tracks is very important. In fact, students with higher PISA literacy scores are less likely to drop out, and less likely to enroll into a vocational field with higher intellectual level, but the level of literacy does not have a direct effect on the probability of finding an adequate job, but only though the vocational track choice. Plug and Groot (1998) argue that even if initial difference in employment probabilities between apprentice tracks and vocational tracks are present, this fades off as people age. Using data from the Netherlands they find no differences between the two tracks in earnings or earnings growth and no differences in employment opportunities in the long run. So even though smoother school to work transition is apparent for apprentices, this advantage fades off in the long run, and is not present in other outcomes.

Noelke and Horn (2011) study Hungary after the transition, when the number of apprentice training places has dropped significantly. Using the fact that the decrease in training places were different in the different counties they conclude that apprentices are less likely to be unemployed after they enter the labor market, which effect fades out after labor market entrance. The authors find no differences in the quality of job. Parey (2009) also uses variation in the supply of apprenticeship places in local labor markets as an exogenous predictor for individuals' choice between firm-based apprentice training and fully school-based vocational program to identify the returns to apprentice training. Similarly to the above listed papers, he shows that apprenticeship training leads to substantially lower unemployment rates, which fade out over time.

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 108932 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 in 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 school-year 2006/7, and subsequent waves have been fielded on a yearly basis. Currently there are 6 waves available with fairly large response rates. The sample appreciation on average is around 5% (see table 1).

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 (represenative 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%)

The HLCS database contains detailed information on skills (literacy and numeracy in 8th grade as well as class marks in each year), ethnicity, school trajectory, family background including parental education and income and many other dimensions. 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 education needs (SEN) are overrepresented in the data, propensity weights are used to control for the oversampling and the imminent sample attrition in the estimations. The HLCS database also has a fully representative subsample (7218 of the 10022 students in 2006/07). This subsample is used – with weights for sample attrition – for robustness checks.

To adjust for sample attrition, propensity weights, which were designed to adjust for non-response and for the oversampling of low-status students in the initial sample, were recalculated for each wave. The same stratifying procedures were used as in the initial sample. The three strata are: 1) 3 settlement types: the capital and big cities, other cities, villages 2) 7 Nuts-2 regions 3) Reading literacy test scores (30 equal groups from the NABC 2006 reading literacy distribution).

The most important variables of interest in this paper are the school track, the apprentice status and the labor market outcome. School track is defined as the student's school track in the fourth wave of the study (see "Hungarian VET system" below), the year when the median student was finishing the last year of compulsory schooling. Vocational students could either do their practical training within school in class or in a school workshop, or could go to a private firm either with the help of the school (usually in groups) or by organizing the training by themselves. I have labeled the former two as school-based and the latter two as workplace-based training. Anyone, who did workplace-based training in the 4^{th} wave or in the 5^{th} wave of the study, is considered an apprentice. The four type of labor market outcomes - employed, unemployed, studying and other - are considered in the last (available) wave of the study and are self-declared. The main reason for this is that the vast majority of students in the 5^{th} wave

(2010/11) were still in school, even within the vocational training students (see table 2 below). By the school year 2011/12 the majority of vocational training graduates have entered the labor market (be employed or unemployed) and only a little less than a quarter of them are still in school (e.g. in further training).

Table 2: Labor market outcomes in the 5th and 6th wave

	5th wave					6th wave				
	work	unempl.	study	other	**Total**	work	unempl.	study	other	**Total**
academic (8-yr)	56	54	2525	96	**2731**	155	48	2429	39	**2671**
%	2,05	1,98	92,46	3,52	**100**	5,8	1,8	90,94	1,46	**100**
academic (6-yr)	212	28	4358	121	**4719**	255	96	4214	151	**4716**
%	4,49	0,59	92,35	2,56	**100**	5,41	2,04	89,36	3,2	**100**
academic (4-yr)	838	775	23360	837	**25810**	2795	1331	20538	1278	**25942**
%	3,25	3	90,51	3,24	**100**	10,77	5,13	79,17	4,93	**100**
voc. sec.	1642	1676	30517	909	**34744**	7220	4975	19633	2568	**34396**
%	4,73	4,82	87,83	2,62	**100**	20,99	14,46	57,08	7,47	**100**
voc. tr.	1647	2066	11306	664	**15683**	6794	3581	3642	1430	**15447**
%	10,5	13,17	72,09	4,23	**100**	43,98	23,18	23,58	9,26	**100**
spec. voc. tr.	191	369	2441	130	**3131**	736	517	1558	281	**3092**
%	6,1	11,79	77,96	4,15	**100**	23,8	16,72	50,39	9,09	**100**
Missing	2797	4462	12127	2804	**22190**	6716	4807	7623	3173	**22319**
%	12,6	20,11	54,65	12,64	**100**	30,09	21,54	34,15	14,22	**100**
Total	7383	9430	86634	5561	**109008**	24671	15355	59637	8920	**108583**
%	6,77	8,65	79,47	5,1	**100**	22,72	14,14	54,92	8,21	**100**

Note: the table contains the weighted number of students

Besides labor market outcomes net income and the length of employment contract are also used as outcome measures.

Other variables that are used are the standardized test score (literacy and numeracy), class mark averages (1- fail to 5- excellent), gender (0 male, 1 female), SEN status, roma ethnicity, and parental education are all from the first wave of the study. Additional controls are the class mark average from the 4th wave, whether the student was in the 12th grade in the fourth wave (a proxy for repeating class) and whether s/he applied to her/his 9th grade school in the first place (proxy for motivation) (see table 3)

Table 3: Descriptive statistics – students in the 6th wave of HLCS

Full sample						
Variable	*obs.*	*weighted obs.*	*mean*	*s.d.*	*min.*	*max.*
math test score (std.)	6453	103298	-0.02	1.04	-3.16	3.08
reading test score (std.)	7002	108583	-0.10	1.03	-3.78	2.87
8th grade class mark average	6754	104920	3.87	0.73	1	5
12th grade class mark average	5463	87557	3.70	0.68	2	5
female	5367	86074	0.49	0.50	0	1
SEN student	7001	108573	0.06	0.25	0	2
roma	7002	108583	0.06	0.24	0	1
parents' ed.: below primary	6992	108484	0.01	0.10	0	1
parents' ed.: primary	6992	108484	0.11	0.31	0	1
parents' ed.: secondary	6992	108484	0.35	0.48	0	1
parents' ed.: tertiary	6992	108484	0.25	0.43	0	1
12th grader in 4th wave	5357	86358	0.85	0.35	0	1
9th grade track is first choice	6369	97572	0.77	0.42	0	1
Vocational training students only						
Variable	*obs.*	*weighted obs.*	*mean*	*s.d.*	*min.*	*max.*
math test score (std.)	1087	14180	-0.83	0.68	-2.74	2.10
reading test score (std.)	1217	15447	-0.92	0.68	-3.78	1.21
8th grade class mark average	1170	14883	3.18	0.53	1	5
12th grade class mark average	1217	15447	3.32	0.58	2	5
female	1194	15143	0.35	0.48	0	1
SEN student	1216	15437	0.10	0.32	0	2
roma	1217	15447	0.09	0.29	0	1
parents' ed.: below primary	1214	15412	0.02	0.15	0	1
parents' ed.: primary	1214	15412	0.20	0.40	0	1
parents' ed.: secondary	1214	15412	0.25	0.43	0	1
parents' ed.: tertiary	1214	15412	0.05	0.22	0	1
12th grader in 4th wave	1217	15447	0.78	0.41	0	1
9th grade track is first choice	1196	15210	0.73	0.44	0	1

The Hungarian VET system

The Hungarian education system resembles that of the post-Soviet systems (see figure A1 in the appendix). Most students choose between three tracks at the end of their 8th grade[2]: an academic track (*gimnázium*), and two vocational tracks. The vocational secondary track (*szakközépiskola*) mixes academic and vocational training and allows for tertiary entrance

[2] 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. More on this see Horn (2013).

after graduation, while the vocational training track (*szakiskola*) is a “dead-end”, but either school-based or workplace-based vocational practical training is compulsory. Table 4 below shows the transition between 8th grade and 9th grade for the cohort included in the HLCS data. Little more than 35% of the cohort enters academic secondary tracks, with around 8% already there (in the early-selective tracks). The other two-third of students goes to vocational tracks. A large majority of vocational students (over 40% of the cohort) enter the vocational secondary, while around 20% end up in vocational training tracks. The remaining less than 5% of students are either dropouts, repeaters or students with special education needs (SEN) enrolled in special vocational training tracks.

Table 4: Transition from 8th to 9th grade (from 2006 to 2007)

		primary	ac. (8-yr)	ac. (6-yr)	Missing	Total
9th grade	**primary school**	454	17	15	33	**519**
	%	0,42	0,02	0,01	0,03	**0,47**
	academic (8-yr)	318	2945	45	92	**3400**
	%	0,29	2,7	0,04	0,08	**3,11**
	academic (6-yr)	450	72	4884	197	**5603**
	%	0,41	0,07	4,47	0,18	**5,13**
	academic (4-yr)	27895	256	264	773	**29188**
	%	25,53	0,23	0,24	0,71	**26,71**
	voc. sec.	42546	274	270	1644	**44734**
	%	38,94	0,25	0,25	1,5	**40,94**
	voc. tr.	20693	83	22	739	**21537**
	%	18,94	0,08	0,02	0,68	**19,71**
	spec. voc. tr,	2103	18	0	143	**2264**
	%	1,92	0,02	0	0,13	**2,07**
	Missing	1794	41	60	124	**2019**
	%	1,64	0,04	0,05	0,11	**1,85**
	Total	96253	3706	5560	3745	**109264**
	%	88,09	3,39	5,09	3,43	**100**

HLCS data, own calculations
Note: sample weighted to represent the whole 2006/8th grade cohort

The vocational training (VT) tracks are considered to be the lowest ranked in the hierarchy of tracks. Hermann (2013) has shown that vocational training tracks are also of worse quality:

students suffer substantial losses in literacy and numeracy between grades 8 and 10 as opposed to the other two tracks. So comparing VT apprentices with non-VT students would bring up several methodological problems. Nevertheless the question remains: can workplace-based training improve the labor market prospects of non-college bound VT students?

Table 5.: Number and percentage of VT students in school-based and workplace-based training by industry

	Unweighted				Weighted			
Industry	school-based	work-based	missing	**Total**	school-based	work-based	missing	**Total**
social services	3	6	0	**9**	24	81	0	**105**
%	33,33	66,67	0	**100**	22,86	77,14	0	**100**
mechanics	108	112	4	**224**	1210	1341	41	**2592**
%	48,21	50	1,79	**100**	46,68	51,74	1,58	**100**
industry	124	106	2	**232**	1356	1193	10	**2559**
%	53,45	45,69	0,86	**100**	52,99	46,62	0,39	**100**
transport-environment	13	19	0	**32**	108	230	0	**338**
%	40,63	59,38	0	**100**	31,95	68,05	0	**100**
services	121	267	7	**395**	1374	3160	88	**4622**
%	30,63	67,59	1,77	**100**	29,73	68,37	1,9	**100**
agriculture	43	29	0	**72**	462	398	0	**860**
%	59,72	40,28	0	**100**	53,72	46,28	0	**100**
missing	178	296	33	**507**	1483	2628	260	**4371**
%	35,11	58,38	6,51	**100**	33,93	60,12	5,95	**100**
Total	590	835	46	**1471**	6017	9031	399	**15447**
%	40,11	56,76	3,13	**100**	38,95	58,46	2,58	**100**

The Hungarian law on vocational training[3] allows schools as well as individuals to contract with firms to provide practical training, but it does not require schools to rely only on private training. Firms that train a sufficient number of students are exempted from paying the compulsory vocational training contribution, and maybe even receive money from the national fund, if they meet certain requirements. Although legally apprentice training is not occupation specific, some industries offer a little more workplace-based training than others. Around two-thirds of VT students in the service sector do their practical training at a private firm, while only around 40% of students with qualifications in agriculture practice outside the

[3] Law of 1993/LXXVI

school. The workplace-based/school-based practical training ratio is rather balanced in the other industries (mechanics, industry, transport and environment) while there are only 9 VT students with qualifications in the social service sector[4] (see table 5).

Does workplace-based training increase labor market outcomes?

The base model is a multinomial logit model with all four possible outcomes – employed, unemployed, studying and other – on the left hand side. Due to the fact that the right hand side variables are measures before the left hand side variable reverse causality is unlikely. In order to minimize omitted variable bias all controls presented in table 3 are included in all the models. The most important, and most unique, controls are the standardized test scores (proxy for skills), which are measured before students enter the secondary tracks. Note that these test scores must not be used for the secondary level entrance.[5] In addition to this the 8th grade class marks – which are given by the teachers, and are used for secondary entrance – and the 12th grade class marks are also utilized. Parental background effects are proxied by parental education. Roma ethnicity, and SEN status as well as grade repetition is controlled for. Motivation is measured by the variable of "9th grade track is first choice" assuming that those, who were accepted to the track of their first choice are more motivated. The month when the survey was taken are also controlled for in all estimations and not shown. Table 6 below presents the same base model on three different samples: the full sample with population weights, without weights and the representative subsample with weights for sample attribution.

[4] The industry classification comes from the students' OKJ (Orszagos Kepzesi jegyzek – National Training Register) code, which they receive when awarded the degree. Although the HLCS questionnaire has asked for the OKJ qualification even it has not been awarded (What qualification are you studying for?) the number of missing values for this question is large: 507 (34.5%) missing of the total of 1471 (100%) responses. The OKJ code was grouped into the six broad industry categories (see Appendix B for details).

[5] It is used to make schools accountable and to provide feedback for the teachers (see OECD 2010).

Table 6: Base model: multinomial logit model, odds of being employed, studying or other wrt. being unemployed

	with weights			without weights			representative sub-sample		
VARIABLES	work	study or trainee	other	work	study or trainee	other	work	study or trainee	other
apprentice	1.581***	1.097*	1.161*	1.776***	1.242	1.061	1.661**	1.080	1.315
	(0.0769)	(0.0604)	(0.0966)	(0.307)	(0.242)	(0.300)	(0.376)	(0.281)	(0.507)
8th grade class mark avg.	1.251***	1.350***	1.411***	1.286	1.444*	1.047	1.110	1.453	1.048
	(0.0635)	(0.0769)	(0.123)	(0.239)	(0.300)	(0.316)	(0.270)	(0.401)	(0.407)
12th grade class mark avg. (1st semester)	1.094**	1.656***	1.403***	1.148	1.628***	1.431	1.101	1.569*	1.166
	(0.0481)	(0.0814)	(0.104)	(0.180)	(0.287)	(0.372)	(0.225)	(0.362)	(0.389)
math test score (std.), 8th grade	0.951	0.952	0.995	1.133	1.115	1.018	0.966	0.944	1.114
	(0.0390)	(0.0444)	(0.0723)	(0.172)	(0.190)	(0.262)	(0.187)	(0.207)	(0.368)
reading test score (std.), 8th grade	0.807***	1.074	0.680***	0.898	0.977	0.664	1.126	1.430	0.656
	(0.0335)	(0.0510)	(0.0488)	(0.137)	(0.170)	(0.172)	(0.218)	(0.320)	(0.217)
parents' ed.: primary or below	0.540***	0.484***	0.694***	0.690*	0.657	0.936	0.488**	0.635	0.502
	(0.0322)	(0.0348)	(0.0688)	(0.152)	(0.169)	(0.322)	(0.137)	(0.208)	(0.235)
parents' ed.: secondary or higher	1.014	1.289***	1.532***	0.885	1.116	1.520	0.996	1.268	1.534
	(0.0585)	(0.0828)	(0.158)	(0.182)	(0.255)	(0.547)	(0.275)	(0.400)	(0.746)
SEN student	0.749*	0.802	2.06e-07	0.901	0.757	9.01e-07	0.470	0.644	4.87e-06
	(0.113)	(0.149)	(0.000105)	(0.398)	(0.415)	(0.000565)	(0.415)	(0.770)	(0.00207)
roma	0.821**	0.999	3.277***	0.856	0.787	2.472**	0.835	1.352	3.001**
	(0.0691)	(0.0995)	(0.373)	(0.250)	(0.275)	(0.952)	(0.331)	(0.593)	(1.586)
9th grade track is first choice	1.014	1.009	1.079	0.918	0.982	0.926	0.837	0.830	0.725
	(0.0541)	(0.0617)	(0.0965)	(0.178)	(0.218)	(0.283)	(0.215)	(0.244)	(0.291)
12th grader in 2009	1.941***	0.616***	0.774***	1.705**	0.621**	0.581	1.993**	0.557*	0.784
	(0.121)	(0.0390)	(0.0760)	(0.380)	(0.142)	(0.192)	(0.601)	(0.168)	(0.365)
female	0.552***	1.022	10.46***	0.455***	0.985	8.203***	0.434***	0.797	6.860***
	(0.0300)	(0.0621)	(1.162)	(0.0902)	(0.214)	(3.005)	(0.109)	(0.228)	(3.240)
Constant	0.399***	0.140***	0.00610***	0.440	0.112**	0.0236***	1.039	0.207	0.0669*
	(0.0827)	(0.0327)	(0.00226)	(0.330)	(0.0957)	(0.0298)	(1.038)	(0.237)	(0.110)
Net number of observations	970	970	970	992	992	992	592	592	592
Weighted number of observations	12,945	12,945	12,945						

Standard error in parentheses, *** p<0.01, ** p<0.05, * p<0.1, ORs reported, reference category is *unemployed*. The month of the survey in 2011 is controlled

The three estimations offer very similar results. Naturally, most variables in the weighted sample are more significant that in the other two estimations, but the odds ratios are very similar in all cases. For the purposes of this study the most important variable – apprentice – is significant in all three estimations and show that those VT students, who had done practical training at a private firm as opposed to doing practical training in school have around 1.6 times higher odds of being employed, as opposed to being unemployed. Parental education, gender and class mark averages in 12th grade are the other three variables that are significant across all specifications.

The baseline uncontrolled average probability of being employed for a VT student in 2011 is 44%. Apprentices, however have 47% chance, while school-based trained students a 39,5% chance of being employed. The chances of being unemployed is reverse: apprentices have a 21% while the others a 26.5% chance. There are no differences in the uncontrolled average baseline probabilities of other two outcomes between the two groups (study: 24%, other: 9%). Using the above model (table 6, weighted model) to predict the probabilities, yields very similar results. The average predicted probabilities for apprentices is 47,5%, while for school-trained 38,7%. The respective predicted probabilities at means are 48,9% and 39,2%, thus the sample distribution is not highly skewed. The marginal effect of being trained at a private firm is 9,6% at the mean. This effect is very similar for the top of the range students (high class mark averages, high literacy and numeracy and parents with secondary general or tertiary schooling) as well as for the bottom ones (low class mark averages, low literacy and numeracy and parents' education primary or below). While the marginal effect for the first type is 8,2% for the second it is 10,8%, and both are highly statistically significant.

The effectiveness of workplace-based training can depend very much on the type of the industry. The HLCS contains information on the type of the qualification for vocational graduates, although the number of missing cases is high (see table 5). Of the 1471 VT students only 964 has this information in the dataset. Table 7 below shows the same multinomial logit model with industry fixed effects added.[6]

Table 7: Multinomial logit model with industry fixed effects, odds of being employed, studying or other wrt. being unemployed

VARIABLES	work	weighted study-trainee	other	work	representative subsample study-trainee	other
apprentice	1.775***	0.985	1.363***	2.060***	0.924	1.196
	(0.0823)	(0.0482)	(0.130)	(0.430)	(0.202)	(0.487)
social services	0.306***	0.841	0.167***	1.78e-07	0.765	4.85e-08
	(0.0674)	(0.136)	(0.0511)	(0.000189)	(0.636)	(0.000117)
mechanics	1.583***	1.359***	0.813	1.867**	1.110	0.611
	(0.103)	(0.0973)	(0.164)	(0.549)	(0.361)	(0.494)
industry	1.266***	1.157**	1.094	1.558	1.072	0.683
	(0.0799)	(0.0796)	(0.153)	(0.444)	(0.332)	(0.404)
transport-environment	2.882***	2.156***	2.75e-07	1.762	2.143	9.56e-07
	(0.496)	(0.403)	(0.000221)	(1.097)	(1.393)	(0.000967)
services (reference)						
agriculture	1.267**	2.000***	2.334***	2.182	4.092***	2.406
	(0.123)	(0.194)	(0.340)	(1.058)	(1.904)	(1.691)
Constant	0.375***	0.613**	0.426**	1.207	1.278	5.376
	(0.0785)	(0.133)	(0.177)	(1.177)	(1.295)	(9.385)
Net number of observations	681	681	681	681	681	681
Weighted number of observations	15,824	15,824	15,824	803	803	803

Standard error in parentheses, *** p<0.01, ** p<0.05, * p<0.1, ORs reported, reference category is *unemployed*. Controls not shown: class marks, test scores, parents education, SEN, roma, female, 9th grade track choice, 12th grader in 4th wave

The main conclusion does not change even if industry fixed effects are controlled for: apprentices have a 1.7 times higher odds to be employed vs. being unemployed in 2011 spring than those with only school-based vocational training practice. Table 8 shows the predicted probabilities and marginal effects of apprenticeship for a student with qualifications in the different industries at the population mean and at the industry means. While the probability of

[6] Note that due to the large missing values of industry codes I recalculated the sample weights with the inverse ratio of having a qualification using the original sampling strata, and hence the larger weighted number of observations.

being employed differs a lot between industries the effect of workplace-based training remains stable across industries.

Table 8: Predicted probabilities and marginal effects for the different industries at the mean.

	Predicted probability		Marginal effect	Marginal effect
	school-based training	workplace-based training	workplace-based training	workplace-based training
	at population mean		at population mean	at industry mean
social services	0,148	0,236	0,092	0,139
mechanics	0,404	0,546	0,144	0,145
industry	0,371	0,511	0,142	0,145
transport-environment	0,480	0,624	0,143	0,146
services	0,336	0,473	0,139	0,141
agriculture	0,291	0,420	0,132	0,145

The non-difference of apprentice effect in the different industries is also underlined if workplace-based training and industry product term interaction are included in the model. Since interaction terms in non-linear models are problematic (Ai and Norton 2003), I have estimated linear probability models[7] on the probability of being employed (1) vs. unemployed, studying or other (0) with industry and apprentice interactions (table A1 in the Appendix).[8] The results show that although the effect of apprentice training is statistically significant only in mechanics, services and agriculture the effects do not significantly differ between any two industries, except industry and mechanics on the 10% level (table A2).

Robustness checks

Although reverse causality and omitted variable bias are not likely in the base model, robustness checks below can highlight whether the results are not driven by the model specification or by the measured outcome. In the first test I have included school fixed effects to the base model as well as to the industry fixed effect model. Note that the HLCS has not

[7] Note that the critique of Horrace and Oaxca (2006) that linear probability models are inherently biased might be less important here, since most of the independent variables are dummies, thus out of sample prediction is less likely (and see also Angrist and Pischke 2008).
[8] Estimating the same models on the probability of being employed (=1) vs. unemployed (=0) offers substantively the same results.

used schools as sampling units, thus the fact that some students are from the same school are by chance only. In fact the 1471 VT students are from 295 VT schools, providing, on average, about 5 students per school for the test. Also since the multinomial logit model with large number of fixed effects has not yet been fully developed (see Pforr 2011), I have estimated linear probability models as well as logit models with fixed effects for this robustness check. Moreover, since fixed effect logit models in Stata cannot deal with within group weights, the representative subsample had to be utilized. All these limitations make this robustness test very restrictive. Nevertheless, the effect of apprentice training remained significant in the non-linear specification without industry fixed effects. Also the size of the effect (odds ratio around 1.8) is very similar to that of the base model. While the average marginal effects of apprenticeship, provided by the linear probability model, have lost its significance, it is still positive, with its size dropped to being around 5% (table 9).

Table 9: Robustness check with school fixed effects

	employed=1, unemployed, studying or other=0			
VARIABLES	linear		logit+	
apprentice	0.0513	0.0512	1.876**	1.841
	(0.0404)	(0.0522)	(0.557)	(0.766)
school FE	y	y	y	y
industry FE	n	y	n	y
Constant	0.455***	0.110		
	(0.154)	(0.280)		
Observations	959	676	397	243
R-squared	0.439	0.509		
Number of schools	253	215	96	67

+ Note that weights varying within category cannot be used for FE panel logit, thus the representative subsample is utilized

Standard errors in parentheses

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

Controls not shown: class marks, test scores, parents education, SEN, roma, female, 9th grade track choice, 12th grader in 4th wave, month of survey in 6th wave

A less restrictive, but maybe more plausible test is in table 11 below. The same multinomial logit model is used as in the base model but apprentice training is split into two years: those who were trained in the 4th wave and those who were trained in the 5th wave (table 10).

Table 10: Number of apprentices in the 4th and 5th wave[9]

		Apprentice 5th wave			
		No	Yes	missing	Total
apprentice 4th wave	No	205	120	252	577
	Yes	62	388	369	819
	missing	13	16	46	75
	Total	280	524	667	1471

Table 11 and 12 highlights that apprentice training has a strong effect on the probability of being employed, even for those, who had training after finishing compulsory schooling. Students enrolled in workplace-based training in the 5th wave of the study (after the median student finished compulsory education) have on average 8% higher chance of being employed in the next year, ceteris paribus the effect of workplace-based training in the 4th wave and 5th wave employment status. This effect is also constant across industries.[10]

Table 11: Multinomial logit model with and without industry fixed effects, odds of being employed, studying or other wrt. being unemployed

	(1)			(2)		
VARIABLES	work	study-trainee	other	work	study-trainee	other
employed in 5th wave	2.391***	0.0394***	1.054	2.391***	2.39e-08	7.08e-08
	(0.193)	(0.0135)	(0.161)	(0.364)	(1.57e-05)	(9.34e-05)
apprentice in 5th wave	1.881***	1.784***	0.921	1.780***	1.270***	1.306**
	(0.103)	(0.110)	(0.0926)	(0.0903)	(0.0681)	(0.137)
apprentice in 4th wave	1.193***	0.762***	1.107	1.369***	0.776***	1.079
	(0.0613)	(0.0453)	(0.0977)	(0.0699)	(0.0419)	(0.113)
industry FE	n	n	n	y	y	y
Constant	0.278***	0.133***	0.00574***	0.0648***	0.594*	0.0880***
	(0.0584)	(0.0319)	(0.00213)	(0.0196)	(0.158)	(0.0444)
Net number of observations	972	972	972	679	679	679
Weighted number of observations	12,708	12,708	12,708	15,771	15,771	15,771

Standard error in parentheses, ORs reported, weighted regressions
*** p<0.01, ** p<0.05, * p<0.1
Controls not shown: class marks, test scores, parents education, SEN, roma, female, 9th grade track choice, 12th grader in 4th wave, month of survey in 6th wave

[9] Note that in the estimation below, students with missing apprentice data in the 5th wave were coded as 0, since they are not in school, and hence not asked this question. 5th wave employment is controlled for.
[10] Note that the number of cases in social services is very small (see table 5).

Table 12: Marginal effect of apprenticeship on being employed.

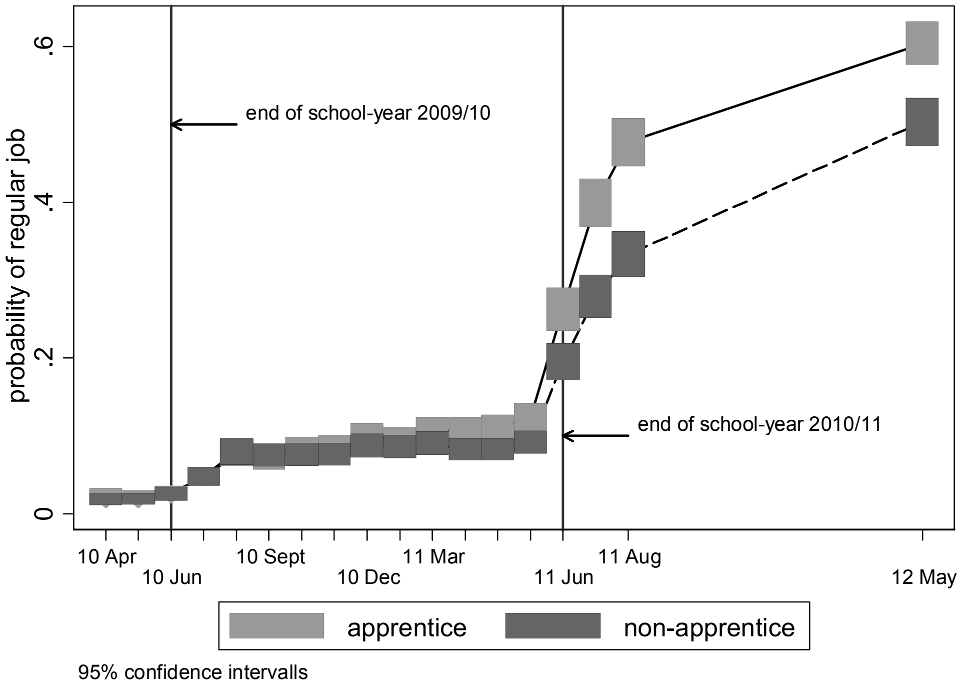
Marginal effect	Model 1 (table 8)		Model 2 (table 8)	
	apprentice in 5th wave	apprentice in 4th wave	apprentice in 5th wave	apprentice in 4th wave
Main effect	0,077	0,080		
social services			0,036	0,038
mechanics			0,090	0,109
industry			0,088	0,103
transport-environment			0,090	0,123
services			0,084	0,094
agriculture			0,067	0,087

Note: marginal effect is calculated for a non-employed, non-apprentice, male, non-roma, non-SEN student with average class marks and test scores, parent with vocational education, who has not repeated class till 12th grade and applied for his track in the first place in 9th grade.

The third robustness check uses another set of outcome variables. The HLCS also asks students about their employment status during the last academic year. That is, students in the 6th wave of the study, in 2012 spring, were asked whether they had had any regular job during the months between 2010 September (the start of the school year) and 2011 August, and students in the 5th wave were asked whether they had a regular job between 2009 September and 2010 August. The data is for each month in between. Figure 1 below depicts the predicted probability for a male, non-roma, non-SEN student with average class marks and test scores, parents with vocational education, who has not repeated class till 12th grade and applied for his track in the first place in 9th grade, and filled the survey in May 2012. The dependent variable is 1 if had a regular job and 0 otherwise.

It seems that apprentices are much more likely to find a regular job right after the end of the school-year. The gap between the average employment probability of apprentices and non-apprentices is growing during the summer months, and do not decline afterwards. This indicates that apprentice VT students have a smoother transition into the labor market than the non-apprentice VT students. The effect is also quite sizeable. It is around 14% in 2011 August (decreasing to 10% in 2010 May), while the average employment probability is around 40%.

Figure 1. Predicted probability of VT students having a regular job

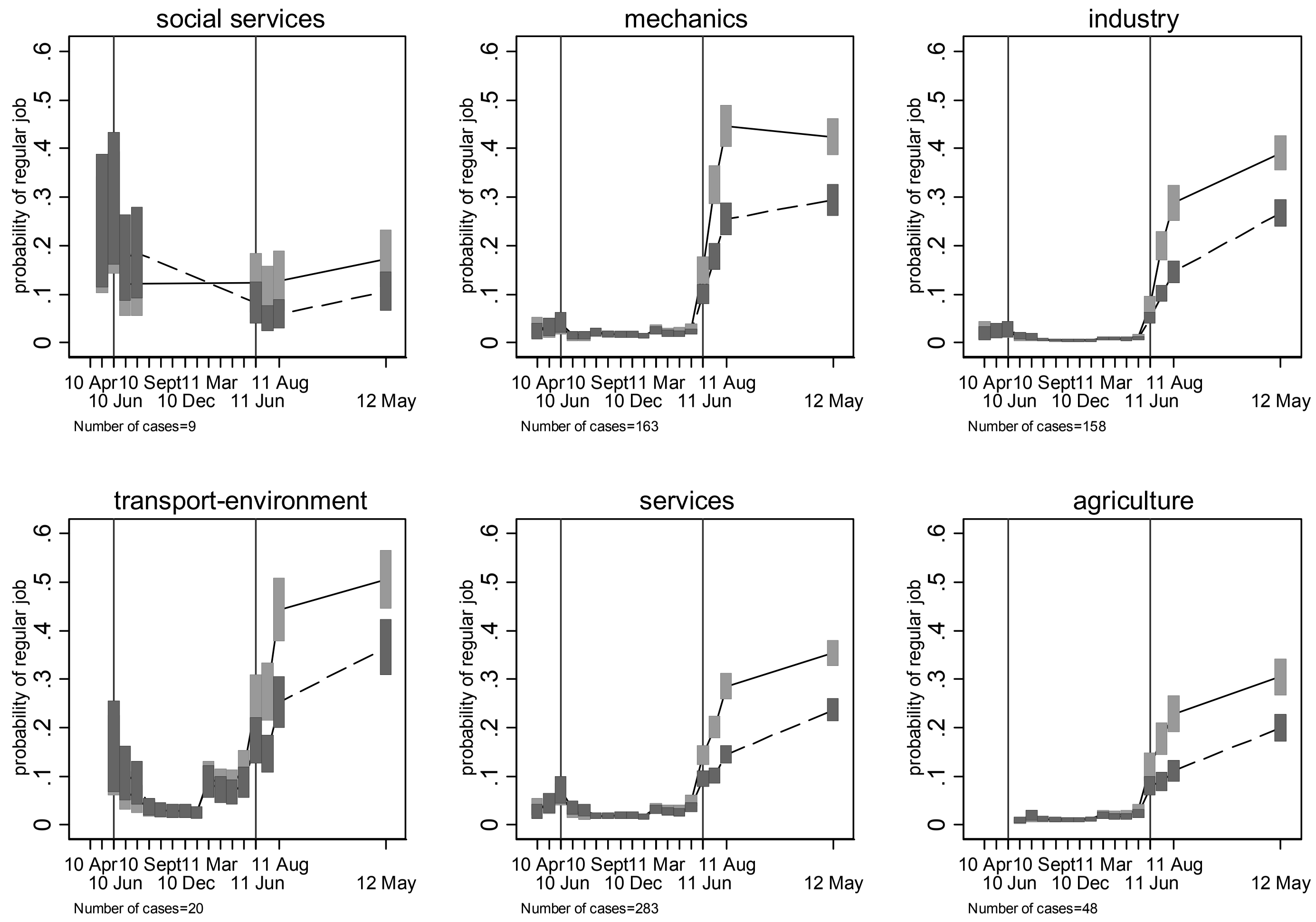


The same pattern is observable within almost all of the industries (figure 2 below). The employment probability gap between apprentices and non-apprentices increase to around 11-20% after the end of the school for the three months and then it either decreases slightly (as in mechanics and transport-environment) or stays at the same level, but remains statistically significant and large.

Whether this effect is due to the superior specific skills that apprentices gained while being trained at the firm or due to the signaling effect, is not clear from these figures. While signaling would predict an immediate and large difference between the groups – because training firms hire the best candidates right away – which should fade away by time, the human capital argument would suggest a steady but continuous increase in the gap, which should only fade away after a good amount of time, when others also gain the specific skills. The increase in the first three months supports the human capital argument, but frictions in the labor market (e.g. summer break at firms) could also explain why the signaling effects takes time to “kick in”. Also the decline (or non-increase) in the differences after the third month would underline the signaling argument, but proponents of the human capital argument could argue that the still remaining 10%+ gap in employment chances could well be the exact reward for superior employer skills.

In order to see whether the signaling or the human capital argument comes closer to reality, other outcomes should also be studied.

Figure 2. Predicted probability of VT students having a regular job, by types of industry



– apprentice - - non-apprentice

Other measures of labor market success

The HLCS allows for three other types of labor market outcome measure: post-compulsory education, net earnings and the type of employer contract (long-term vs. fix-term). As for the post-compulsory education is concerned, the base model and the industry fixed effect models (table 6 and 7) suggest that apprentices are not less likely to stay in education. While apprentices are more likely to be employed, as opposed to being unemployed, the difference between workplace-based training and school-based training is non-significant when the odds of being unemployed vs. enrolling into post-compulsory education or training is compared. In other words, apprentices are not more likely to enter the labor market (be employed or unemployed) than non-apprentices, but when they enter they are more likely to be employed. Table 11, on the other hand, suggests that apprentices taking workplace-based training in the 4^{th} wave, and who are neither employed nor apprentices a year later, are much less likely to study in the 6^{th} wave with respect to being unemployed, i.e. they are more likely to enter the labor market than non-apprentices. Conversely, apprentices in the 5^{th} wave are more likely to be studying as opposed to being unemployed, i.e. less likely to enter the labor market. This suggests that the first group of students might be negatively selected (after being trained could not get a job and could not stay in workplace-based training), while apprentices in the 5^{th} wave profit from training as opposed to non-apprentices either by more likely being employed or by studying. It would – of course – be better if the post-training employment chances of these apprentices could be compared with those with only school-based training and with post-compulsory training, but unfortunately the panel is not (yet) long enough for such an analysis.

The HLCS asks for the average monthly net earnings and the average net wage received from the main job of the respondent. If data for the first question was missing I imputed it with data from the second. Data only for 14 of the total of 511 employed VT students were missing

(2,4% of cases). The uncontrolled mean net earnings for the apprentices were almost exactly the same as for the non-apprentices: 85thousand Hungarian forints (~280 Euro). Table 13 below shows the model where the net earning is regressed on the same controls as in the base model (as in table 6, 1st column). The difference between apprentices and non-apprentices remains insignificant even after controls are included.

As this is a textbook case of the Heckman (1979) sample selection bias – where only the earnings of the employed is observed, and since non-apprentices are less likely to be employed thus the observed mean earning of the non-apprentices are likely to be higher than the unobserved wage offers, which is likely to downwardly bias the effect of apprentice training on observed earnings – I have used both a self-declared reservation wage (net) as well as the Heckman ML correction to see the true effect of apprenticeship on earnings. In Table 13 column 2 the dependent variable is the net earning imputed with the reservation wage for the unemployed. Column 3 and 4 in table 13 shows the Heckman correction for the model in column 1. Although the selection corrected results are somewhat larger, neither of the estimates shows significant effects of apprenticeship on net earnings.

On the other hand, apprentices are more likely to get long-term contracts, as opposed to fix-term contracts, than school-based trained students. While 73% of employed apprentice students have long- term contracts in 2012 spring, the respective figure for non-apprentices is only 62%. Even after controlling for the individual characteristics as in the base model the chance of an average apprentice to get a long-term contract is significantly higher. The average marginal effect is around 16% (table 14, columns 1-2). The effects are substantively the same, even if industry fixed effects are included (table 14, columns 3-4).[11]

[11] I have also estimated a Heckman probit correction model, with no significant sign for selection bias. Not shown here.

Table 13. Other labor market outcomes – net earnings

			Heckman correction	
	net earning			1st stage
VARIABLES		w/ reservation wage	net earning	employed
apprentice	1,201	948.2	8,286	0.240**
	(4,447)	(3,022)	(5,109)	(0.0965)
8th grade class marks	6,799	4,618	7,137	0.0750
	(5,353)	(3,736)	(5,995)	(0.112)
class mark (grade) average, 1st semester	5,786	5,751**	912.3	-0.0380
	(3,940)	(2,470)	(4,294)	(0.0794)
math test score (std.)	1,461	1,382	-762.7	-0.00914
	(3,115)	(2,801)	(3,944)	(0.0755)
reading test score (std.)	3,086	-1,548	-3,675	-0.0979
	(2,856)	(2,300)	(4,082)	(0.0785)
parents' ed.: primary or below	4,031	-5,310	-3,549	-0.134
	(5,508)	(3,795)	(7,045)	(0.130)
parents' ed.: secondary or higher	1,365	5,845	159.7	-0.121
	(5,129)	(3,665)	(5,855)	(0.109)
SEN student	-16,775*	-5,754	-17,495*	-0.0607
	(8,828)	(5,355)	(10,505)	(0.216)
roma	-15,917**	-1,290	-22,221***	-0.229
	(7,784)	(4,992)	(8,373)	(0.151)
current track is first choice	2,840	3,900	2,535	0.0302
	(4,113)	(3,324)	(5,253)	(0.103)
12th grader	6,082	2,644	28,669***	0.492***
	(5,800)	(3,666)	(7,497)	(0.119)
female, NABC 2006	-20,504***	-11,739***	-39,102***	-0.562***
	(4,720)	(3,299)	(7,618)	(0.106)
6.fho	6,280	5,407	5,754	0.0621
	(4,339)	(3,342)	(5,749)	(0.108)
7.fho	9,971	3,219	4,769	0.0120
	(6,115)	(3,618)	(6,432)	(0.124)
8.fho	1,006	1,594	-3,758	-0.152
	(5,848)	(6,847)	(12,421)	(0.228)
Constant	40,084*	44,574***	-11,576	-0.709
	(23,501)	(15,652)	(28,613)	(0.451)
athrho				2.435***
				(0.393)
lnsigma				10.91***
				(0.128)
Observations	414	891	955	955
R-squared	0.087	0.051		

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

These results suggest that signaling effect is more important in getting the first job than skills. If apprentice students had superior skills compared to non-apprentices, firms would most likely offer them a higher amount to compensate for higher productivity. On the other hand if signaling would not matter, the chance for non-apprentices to get a fix-term contract should be just as high as for apprentices. This latter result suggests that firms use apprenticeship training as some sort of a substitute for the probation period. It might well be that “stayers”, i.e. those, who get their first job at the firm where they were apprentices, drive the results, as in case of the France (Bonnal, Mendes, and Sofer 2002).

Table 14. Other labor market outcomes – long term contract

	Linear	Logit+	Linear	Logit+
VARIABLES	long-term contract++		long-term contract++	
apprentice	0.162***	2.080***	0.209***	2.864***
	(0.0593)	(0.128)	(0.0721)	(0.241)
8th grade class mark avg.	-0.0734	0.709***	-0.0440	0.794***
	(0.0636)	(0.0466)	(0.0831)	(0.0658)
12th grade class mark avg. (1st semester)	0.0192	1.097*	0.0238	1.130*
	(0.0464)	(0.0610)	(0.0575)	(0.0822)
math test score (std.), 8th grade	0.0533	1.288***	0.0580	1.316***
	(0.0479)	(0.0694)	(0.0533)	(0.0909)
reading test score (std.), 8th grade	-0.0311	0.871***	-0.0476	0.793***
	(0.0457)	(0.0455)	(0.0517)	(0.0531)
parents' ed.: primary or below	0.00932	1.043	0.0241	1.151
	(0.0749)	(0.0858)	(0.0915)	(0.126)
parents' ed.: secondary or higher	-0.00625	0.965	0.0798	1.542***
	(0.0627)	(0.0676)	(0.0686)	(0.139)
SEN student	-0.0447	0.827	-0.0812	0.629**
	(0.153)	(0.164)	(0.177)	(0.135)
roma	-0.260**	0.327***	-0.267*	0.286***
	(0.104)	(0.0369)	(0.140)	(0.0439)
9th grade track is first choice	0.0204	1.093	-0.0368	0.808**
	(0.0601)	(0.0719)	(0.0652)	(0.0718)
12th grader in 2009	0.0372	1.182*	0.0965	1.585***
	(0.0843)	(0.103)	(0.0966)	(0.177)
female	0.0184	1.090	0.0104	1.035
	(0.0679)	(0.0795)	(0.0880)	(0.109)
Industry FE	n	n	y	y
Constant	0.749***	3.150***	0.543*	0.458
	(0.255)	(0.841)	0.209***	(0.271)
Net number of observations	428	428	291	291
Weighted number of observations		5,693		4,011
R-squared	0.060		0.138	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
+ ORs reported, population weighted++ Long term contract =1 fix term contract=0,

“Stayers” and “movers”

Unfortunately the HLCS does not contain direct information about the exact firm of the apprenticeship. Nevertheless the type of the firm[12] during the apprenticeship as well as the type of the first job is surveyed, but only after the 5th wave. That is, the effect of “moving” can only be estimated for those who had workplace-based training in the 5th wave. Moreover, since these firm categories are very broad this is a better proxy for “moving” than for “staying”, since it is likely that if the industry of the training firm and the employer is not the same, people have moved; however its converse does not mean that apprentices have stayed where they were trained.[13] Table A3 in the appendix shows the number of students within the different apprenticeship/employer type categories. Naturally this variable is only available for those, who were apprentices in the 5th wave and got a job in the 6th wave. Thus only effects in terms of net earnings and long-term contracts can be analyzed. The reference group is non-apprentices, who had a job in 6th grade.

The results seem to underline that signaling has an important effect: “stayers” have a 22-23% higher chance, or 2.8-3.1 times higher odds of receiving a long-term contract as opposed to either “movers” or to non-apprentice students who are employed in 6th wave. The advantage of “movers” as opposed to non-apprentices is less obvious. It is non-significant in the linear, but significant in the logit specification, and the size of the effect is also much smaller, but still sizeable; around 10-15% higher probability or 1.5-2 times higher odds. Nevertheless, movers do have a non-negative or positive advantage, which suggests that increased skills might also matter for finding the first job, or that signaling works across firms as well (maybe

[12] Agriculture, forestry and fishing; Mining and quarrying; Processing; Electricity, gas, steam and air conditioning; Water supply, wastewater collection and treatment, waste management; Construction Trade, automotive services; Transportation, warehousing; Hotels and restaurants, catering; Information, communication; Financial and insurance activities; Real estate transactions; Professional, scientific and technical activities; Administrative and support service activities; Administration and defense, compulsory social security; Education; Human health and social work; Arts, entertainment and recreation; Other services; Households as employers, producers, and service; Organizations outside Hungary; Other;

[13] But if we assume technologically specific skills these categories are useful.

though personal references). On the other hand differences in net-earning – again – are not significant, which downplays the importance of skills (table 14).

Table 14. Stayers vs. movers and non-apprentice employed.

	net earning		long-term contract			
VARIABLES			linear		Logit+	
mover	1,589	2,426	0.102	0.150*	1.545***	2.020***
	(5,469)	(6,220)	(0.0759)	(0.0846)	(0.115)	(0.149)
stayer	7,977	9,352	0.225***	0.236**	2.889***	3.110***
	(6,144)	(6,823)	(0.0852)	(0.0919)	(0.278)	(0.259)
Industry FE	n	y	n	y	n	y
Constant	35,787	46,038*	0.737***	0.635**	2.919***	0.562
	(23,933)	(23,482)	(0.257)	(0.318)	(0.817)	(0.249)
Net number of observations	425	284	438	292	438	292
Weighted number of observations					5,828	6,734
R-squared	0.100	0.093	0.054	0.132		

Robust Standard errors in parentheses, +ORs reported, weighted regressions
*** p<0.01, ** p<0.05, * p<0.1
Controls not shown: class marks, test scores, parents education, SEN, roma, female, 9th grade track choice, 12th grader in 4th wave, month of survey in 6th wave

Conclusion

Although workplace-based training has long been praised for its effectiveness in preparing non-college bound youth for the labor market, there are but a handful of studies that could convincingly show that the observed association between apprentice training and higher initial employment probability is causal. This analysis shows that vocational training program graduates, who have done their practical training at private firms (apprentices), are around 10% more likely to be employed after they finished education than those, who had the practical training in schools. This effect is net of individual skills, school attainment, parental background, motivation, gender and ethnicity. The effect is also very similar across industries, and is likely to remain significant and large during the first year in the labor market.

On the other hand, there seems to be no difference between the net earnings of apprentice and non-apprentice students after they are employed, which suggests that there are no significant differences in specific skills between these two groups. However, the difference between the two groups in getting a long-term contract with their employer is significant and sizeable. Apprentices are 16-20% more likely to sign a long-term contract as opposed to the non-apprentices, which suggests that firms might use the training period as a probation period. Hence apprenticeship might only be effective due to the increased signals it provides. Comparing those, who might have stayed at the same firm, where they were trained with those, who moved to another type of sector shows that "stayers" are more likely to get long term contracts but not more likely to earn more money. On the other hand "movers" also have a higher probability to get a long term contract as opposed to non-apprentices, but also do not earn more money.

All in all, this study argues that the positive effect of workplace-based training on initial employment probability is causal, but it is more likely to be due to the signal that apprentice training sends that the increased specific skills that it provides.

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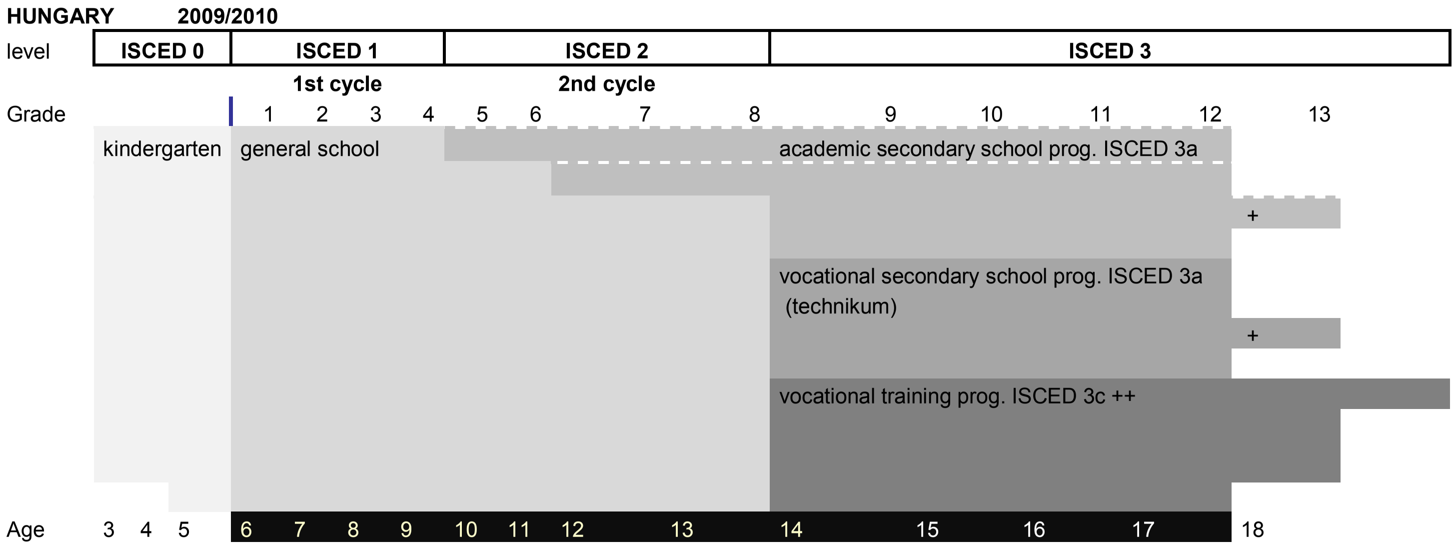
Appendix A

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 2012 September: until the age of 16)

vocational secondary school programmes 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 programmes are also available for elementary school drop-outs

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

Table A1: Linear probability model with industry and apprenticeship interactions, AME of being employed vs. being unemployed, studying or other (weighted)

	(1)
VARIABLES	employed=1
Interactions	
Social services * apprentice=0	-0.0527
	(0.374)
Social services * apprentice=1	-0.123
	(0.116)
Mechanics * apprentice=0	-0.0801
	(0.0931)
Mechanics * apprentice=1	0.138
	(0.0904)
industry * apprentice=0	ref.
industry * apprentice=1	-0.00618
	(0.0938)
transport-environment * apprentice=0	0.153
	(0.232)
transport-environment * apprentice=1	0.142
	(0.179)
services * apprentice=0	-0.0965
	(0.0954)
services * apprentice=1	0.0322
	(0.0776)
agriculture * apprentice=0	-0.220*
	(0.114)
agriculture * apprentice=1	0.0675
	(0.137)
Constant	0.286
	(0.211)
Observations	681
R-squared	0.109

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Controls not shown: class marks, test scores, parents education, SEN, roma, female, 9th grade track choice, 12th grader in 4th wave, month of survey

Table A2: Does the effect of apprentice training differ between industries?
Significance (p-values) of F-tests, comparing the effects of apprenticeships between industries as estimated in table A1. Diagonal elements show the p-value of apprenticeship training within industries.

	social services	**mechanics**	**industry**	**transport-environment**	**services**	**agriculture**
social services	0,85					
mechanics	0,46	*0,02*				
industry	0,87	*0,09*	0,95			
transport-environment	0,90	0,43	0,99	0,97		
services	0,61	0,45	0,27	0,63	*0,09*	
agriculture	0,38	0,69	0,10	0,34	0,35	*0,06*

Table A3: Types of training and employer firms and the number of individuals

			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	mis	total
5th wave trainer	1	Agriculture, forestry and fishing	**1**	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	12	17
	2	Mining and quarrying	0	**0**	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	3	Processing	6	0	**29**	2	0	2	1	0	2	0	0	0	0	0	1	1	0	0	2	0	0	0	0	56	102
	4	Electricity, gas, steam and air conditioning	1	0	0	**7**	1	2	0	1	0	0	0	0	0	0	2	0	0	0	1	0	0	0	1	14	30
	5	Water supply, wastewater collection and treatment, waste management	1	0	2	0	**0**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	5
	6	Construction	10	0	17	1	1	**45**	1	1	1	1	0	0	1	1	4	0	1	0	5	0	0	0	0	81	171
	7	Trade, automotive services	1	0	15	0	0	4	**20**	2	7	0	0	0	0	0	3	0	0	0	8	0	0	0	0	70	130
	8	Transportation, warehousing	0	0	3	0	0	0	3	**1**	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	7	16
	9	Hotels and restaurants, catreing	2	0	10	0	0	1	17	0	**64**	0	0	0	0	0	0	0	1	2	5	0	0	0	0	129	231
	10	Information, communication																									
	11	Financial and insurance activities	0	0	0	0	0	0	0	0	0	0	**0**	0	0	0	0	0	0	0	0	0	0	0	0	4	4
	12	Real estate transactions																									
	13	Professional, scientific and technical activities	0	0	0	0	0	0	0	0	0	0	0	0	**0**	0	0	0	0	0	0	0	0	0	0	1	1
	14	Administrative and support service activities	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**	0	0	0	0	0	0	0	0	0	2	2
	15	Administration and defense, compulsory social security	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**3**	0	0	0	0	0	0	0	0	1	4
	16	Education	0	0	3	0	0	0	2	0	0	0	0	0	0	0	1	**0**	0	0	0	0	0	0	0	9	15
	17	Human health and social work	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**	0	0	0	0	0	0	21	24
	18	Arts, entertainment and recreation	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	**0**	0	0	0	0	0	1	3
	19	Other services	2	0	7	0	3	3	5	2	8	0	0	0	0	1	3	0	1	0	**19**	0	0	0	1	70	125
	20	Households as employers, producers, and service	0	0	1	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**	0	0	0	0	3
	21	Organizations outside Hungary																									
	22	Other																									
	23	Don't know	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	6	8
		missing	211	2	443	24	46	154	345	71	213	33	40	1	12	25	154	23	54	58	226	11	1	4	12	6,967	9,13
		total	235	2	533	34	52	213	395	78	296	34	40	1	13	27	173	25	59	60	269	11	1	4	14	7,453	10,022

Appendix B

The official list of OKJ qualifications contains of 21 larger categories. I have grouped these into 6 broad categories (industries) in order to increase the number of cases within each category but still facilitate relevant comparison between the groups

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