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Abstract

When information about the true abilities of job-seekers and applicants are hard to get, statistical discrimination by employers can be an efficient strategy in the hiring and wage setting process. But statistical discrimination can induce costs, if labor relations cannot be terminated in the short term and wages are fixed over a certain period. In this paper we use a unique longitudinal survey that follows the PISA 2000 students in their educational and work-life career. We test whether deviance in the PISA test scores from what one would have predicted based on observable characteristics, influences the probability to succeed in the transition from compulsory school into a firm-based apprenticeship and whether it can explain differences of the individual performances during training. Our results suggest that hard-to-get information plays a significant role in the transition, but not always in a symmetric manner.

JEL-Code: I200, J240, J710.

Keywords: statistical discrimination, school-to-work transition, PISA.

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1. Introduction

Difficulties in identifying the true productive capacity of heterogeneous workers have played an important role in labour economics for a long time. The literature predicts, that in the absence of accurate information on ability, firms will base hiring or wage setting decisions on easy-to-observe signals and thus screen and statistically discriminate on education level, gender, ethnicity or other readily-available factors that are assumed to be correlated with the lacking information (Phelps, 1972; Spence, 1973; Arrow, 1973; Aigner and Cain, 1977). An indirect test of statistical discrimination is provided by the employer learning literature (Farber and Gibbons, 1996; Altonji and Pierret, 1997, 2001), wherein information that is only observable to the researcher, e.g. Armed Forces Qualification Test-scores (AFQT), is found to have increasing influence on wages with workers' experience, indicating that workers' true productivity is gradually revealed over time by the labour market.

In this paper we attempt to investigate the effect of easy-to-observe characteristics and hard-to-observe ability on the success of applicants on the transition from compulsory schooling into apprenticeship training, asking whether and to what extend firms use hard-to-get information about the productive potential in their hiring decision (pre-market employer learning) and whether hard-to-observe ability further unfolds its effect within the apprenticeship training period (employers learning).

Firm-based vocational training is the most common post-compulsory-schooling in Switzerland, with more than two thirds of each cohort opting for this educational pathway. As an apprentice needs to be hired by a firm for the training period, apprenticeship training entails early integration into the labour market (about age 16). Employer's screening devices thus play an important role in the sorting process of youngsters into vocational education. In the public discussion, stereotyping is claimed to play a (too) dominant role in this process. There are not only claims that firms generally show insufficient willingness to offer apprenticeship places and thus force a considerable part of compulsory-school graduates every year into non-certifying scholastic interim solutions, but also are there signs that the process of allocation of young applicants into vocational tracks might discriminate those with unfavourable attributes, as for example those with low parental socio-economic status, migration background or low-level compulsory school track attendance, presumably irrespective of their true ability.

There are at least two good reasons why subsequent training firms effectively may base their hiring decisions on easily observable factors. First, many of individual background characteristics are indeed correlated with true school performance and thus with labour productivity. Second, firms are reluctant to rely solely on educational signals such as school marks and the level of school track at compulsory school, because in the absence of uniform school standards and external exams in Switzerland, grades between schools and classes are not perfectly comparable and therefore potentially poor predictors of the true ability of an applicant. It is therefore only natural to assume that firms build expectations based on other easy-to-observe ability proxies and decide accordingly.

However, although employment decisions solely based on easy-to-observe factors are cheap, they may also be costly. Economic rationale therefore suggests a potentially high interest of firms in seeking hard-to-get ability information before choosing apprenticeship applicants: In contrast to ordinary work contracts, apprenticeship contracts cannot be terminated easily and wages are fixed over a defined period of several years. Furthermore, as compulsory school leavers at age 16 all are newcomers in the world of work, there is no advance information provided by the labour market on the applicant's productive potential. So, in terms of allocative efficiency as well as in terms of equity, the effective achievement potential of a student rather than his outward impression should act as a decisive determinant for his/her further career prospects.

In order to test whether hard-to-observe students' ability is revealed and accounted for within the transition from schooling to market-based upper-secondary education, or whether, alternatively, allocation into vocational tracks is solely based on easy-to-observe factors, we make use of the unique longitudinal data set TREE[1] that comprises PISA-2000 test scores of pupils at age 15 along with individual background characteristics and detailed information on their further educational and working pathways ever since. The competence test of PISA provides us with an ability measure that is only observable to the researcher, but not observed by recruiters of training firms. Following the procedure in Farber and Gibbons (1996) we use the test score information in its orthogonalised form, thus already cleaned from the part that is explainable by observables, leaving the ability component that is hard-to-observe for outsiders.

[1] As of 2008, TREE (Transitions from Education to Employment) is co-funded by the Swiss National Science Foundation (SNSF) and the University of Basel. From 2000 to 2007, the project has been financed and/or carried out by said SNSF, the Departments of Education of the three cantons Berne, Geneva and Ticino, the Federal Office for Professional Education and Technology (OPET), and the Swiss Federal Statistical Office (FSO).

We then go one step further and explicitly differentiate between so called *overachievers* and *underachievers*. This enables us to test whether hard-to-observe ability is revealed (if at all) symmetrically. Thereby we can test separately, whether or not ability information is gathered in favour of those students who appear to be less able than they actually are *(overachievers)* and, whether or not ability is revealed to the disfavour of those students who create an overall outward impression that is better than their actual performance *(underachievers)*.

The reminder of the paper is organised as follows: the next section describes the institutional setting wherein the transition from lower- to upper-secondary education takes place in Switzerland. Section 3 provides an overview of the literature that deals with statistical discrimination, screening, stereotyping and employer learning. In section 4 we formulate the hypotheses. The empirical strategy is described in section 5. Section 6 presents the data along with descriptive information. The empirical results are discussed in section 7. Finally, section 8 concludes with a summary and discussion of our findings.

2. The Swiss education system and the transition into upper secondary levels

2.1. The Swiss education system

Compulsory school in Switzerland comprises 9 school years: 6 years of primary school and 3 years of lower secondary school. There is variation between cantons with respect to the design of schooling models: normally, there is sorting at lower secondary level into different school tracks according to pupils' intellectual ability, based on teachers' recommendations and parental decisions. In the majority of cantons there are three levels: the most intellectually demanding are upper-level school tracks which enable direct entry into Baccalaureate School, then intermediate level tracks, and finally tracks offering basic-level courses. There is considerable variation in the quantitative importance of these different school tracks between cantons and regions, implying that the respective ability thresholds vary, too.

After 9 years of compulsory schooling pupils can choose between several general and vocational education alternatives at upper-secondary level. The majority of a cohort typically follows a vocational track in the form of apprenticeship training that lasts 3 to 4 years, depending on the training occupation. Apprentices do most likely but not exclusively come from the intermediate- and basic-level compulsory school track. Apprenticeship training consists of firm-based on-the-job training (3-4 days a week) in combination with formal education in public vocational schools (1-2 days) and is thus also called "dual" apprenticeship training. It leads to a nationally recognised certificate.

Apart from firm-based vocational education there is also the possibility to acquire equivalent certificates in full-time vocational schools. This option is, however, restricted to certain occupational fields and is more present in Latin Switzerland (French and Italian speaking part).

According to the yearly statistic that counts all entrances into different educational tracks at the post-compulsory level (FSO, 2000), the share of enrolments into vocational tracks amounted to 73.5% of all certifying educations at upper-secondary level in the year 2001, with only a minor part of 11% full-time vocational school entries of all vocational tracks; the rest being firm-based.

Besides vocational education programmes there are different general educational tracks leading to certificates at the upper-secondary level. The share of students that pursue a general education path amounts to 26.5%. About 80% among them are typically enrolled in baccalaureate school programmes, which last 3 to 4 years and provide direct access to academic universities. Baccalaureate programmes are open for those pupils who had either followed an upper-level school track at the lower secondary level or who had followed a medium-level school track and performed well enough to fulfil the academic conditions of admission.

2.2. The transition into apprenticeship training

As noted above, about two thirds of each cohort of compulsory school graduates opt for a dual apprenticeship programme at upper-secondary level. Apprenticeship training requires hiring by an employer willing to train the school leaver (combined training and work contract) and can thus be seen as a regular labour market entry. The searching and selection process for apprenticeship places is comparable to an ordinary job search procedure: firms announce apprenticeship openings, potential apprentices apply for these openings, applicants undergo a selection process with interviews and tests and, finally, either get the apprenticeship or have to continue searching. The latter might be accompanied by a process of adaption of expectations about the aspiration level of apprenticeship track one might be suited for: after unavailingly applying for high-prestigious apprenticeships, applicants might adjust their aspirations downward and begin to apply for less demanding vocational tracks.

Besides business cycle effects that generally tend to affect the yearly amount of apprenticeships in a pro-cyclical way (Brunello, 2009; Muehlemann et al., 2009), the apprenticeship system in Switzerland has proved to be considerably stable over the past decades, succeeding in integrating a vast majority of pupils into post-compulsory education, and later on into the labour market.

However, may be due to ongoing technological change and a shift towards a larger service industry which leads to increased requirements on workers' qualifications, educational prerequisites and social competences, the *immediate* transition from compulsory schooling to vocational education is observed to be less smooth nowadays. The share of a cohort found in non-certifying intermediate school years has increased from 9% to 14% since 1990, with a disproportionately high amount of females among them (FSO, 2007).

There is some concern that finding an apprenticeship place is getting more and more difficult, especially for compulsory school leavers with unfavourable characteristics as for example low-level compulsory school track attendance, bad school marks, migration background, low socio-economic parental status or difficult family situations. As many of these factors are known to be correlated with the academic potential of individuals, it raises the question whether the resulting allocation of young compulsory school graduates into vocational education is solely explainable by easy-to-observe characteristics, or whether hard-to-observe ability affects the transition success of applicants, too.

3. Related Literature

Recruiters of firms only have limited information about the true skills of an applicant. They might try to obtain better information by using screening tests, interviews and other measures, but they all come at a cost. If the costs are high, the concept of statistical discrimination predicts that firms base their hiring decisions on all easy-to-observe indicators that are assumed to be correlated with the missing information (Phelps, 1972; Arrow, 1973; Aigner and Cain, 1977). Examples for inexpensive to observe characteristics are educational credentials, gender, ethnicity, age or school reputation.

Empirically, statistical discrimination is difficult to test, as a significant coefficient of e.g. the ethnicity or gender variable could also reflect taste based discrimination as it was formulated in Becker (1957). However, an indirect empirical test of statistical discrimination is provided by the employer learning literature. Examples are e.g. Farber and Gibbons (1996), who find that the part of AFQ test score information that was not predictable by statistical discrimination at market entry (residualized test score) becomes increasingly correlated with wages as market experience increases. Or Altonji and Pierret (1997, 2001), who simultaneously investigate employer learning and statistical discrimination and find that wages not only become more dependent on a worker's ability (AFQ tests), but at the same time also become less dependent on easily observable characteristics. These results suggest that firms initially form believes about the productivity of a worker by statistical discrimination e.g. on educational credentials and ethnicity, and then, as the true individual productivity is revealed over time, revise believes accordingly.[2]

The focus of all these studies is on symmetric employer learning, that is, all firms in the market are assumed to learn simultaneously. If current employers, however, get better informed about the productivity of their workers (asymmetric learning) then monopsony power of the incumbent firms will affect employees' mobility behaviour and wages (Greenwald, 1986; Gibbons and Katz, 1991). The information asymmetry on workers' ability is also proposed in the literature as a possible source, amongst others, for firm investments in general human capital and thus, under certain conditions, for the existence of vast apprenticeship systems (Acemoglu and Pischke, 1998).

[2] Evidence for employer learning has also been found for Great Britain (Galindo-Rueda, 2003) and, in the case of blue-collar workers, for Germany (Bauer and Haisken-DeNew, 2001).

4. Hypotheses

Unlike the case discussed in employer learning's literature which focuses on employees' unobservable characteristics that reveal themselves gradually, and the literature which discusses the (asymmetric) learning potential on ability as a rational for firms' training investments, we start our analysis by asking whether or not potential employers (successfully) try to get costly information on an trainee's ability even before employing. There are at least two arguments why one would expect training firms to invest considerably into learning about an applicant's productive potential prior to hiring the apprentice: First, the sorting process of young school leavers into firms and occupations is not based on trial and error (job shopping) as for example in the US (see Topel and Ward, 1992) as training contracts have a fixed duration of 3 to 4 years and cannot be terminated as easily as ordinary working contracts. There is little scope for adjustments in terms of training content below a defined level, nor is it possible to downward adjust the training wages that are fixed beforehand for the entire period in the training contract. Second, some apprenticeship training occupations are associated with considerable firm net-investments (Muehlemann et al., 2007; Wolter and Ryan, 2010). Dropouts, e.g. due to a bad match between trainee and the intellectual aspiration level of the apprenticeship track can thus lead to considerable losses for the firm.

Hence, firms might avoid taking a large amount of uncertainty about a trainee's true ability and try do diminish the risk by investing in learning about the true ability before hiring. In fact, it is observed that firms not only do extensive screening on the basis of application letters, school-reports and interviews, but also use own screening-tests similar to PISA-tests or offer trial days ("Schnupperlehren"), where the applicants motivation and working behaviour is observed.

Nevertheless, the outcome of the selection process is, in public and academic discussion, regarded as all or partly depending on some sort of stereotyping, such that for example females, immigrants or low-level compulsory school track graduates are at a disadvantage, regardless of their individual performance potential.

Using PISA-literacy test scores at age 15 as ability information that is only observable to the econometrician, but not to the market, we want to test whether ability which lies above or below the competence level one would predict based on easy-to-observe characteristics has an influence on firms' hiring decision and, additionally, whether it gets further revealed in the subsequent training period.

The analysis will be performed on four dependent variables: First, we want to test whether the probability of finding an apprenticeship place directly after compulsory schooling only depends on easy-to-get information, which would indicate hiring decisions purely based on statistical discrimination. Second, we want to test whether hard-to-observe ability affects the resulting allocation of youngsters into different vocational tracks that vary with respect to the intellectual aspiration level, or whether, again, the success to get a more demanding apprenticeship place solely depends on easy-to-observe characteristics (see Bertschy et al., 2009, for the importance of the aspiration level of the vocational track in the apprenticeship-to-work transition). We then ask whether there is further revealing of hard-to-observe ability *during* the apprenticeship period. We analyse whether the occurrence of problems during training (failure in the final exam, repetition, changes in training occupation or drop out) is related to the part of ability that initially was hard-to-observe for the employer, assuming that, in the case of problematic situations, the employer-employee relationship (apprenticeship contract) might not have been realised if employers had possessed perfect information beforehand. Finally, we look whether hard-to-observe ability is also reflected in the grades of the apprenticeship final examination so that it translates into easy-to-observe information to the labour market.

It is separately tested in each estimation whether hard-to-observe ability components are revealed in an asymmetric manner. That is, we want to allow for the possibility that firms, when evaluating the productive potential of an applicant, treat applicants differently, depending on whether someone is above the ability level one would predict based on observables and vice versa.

5. Empirical Strategy

Transition and apprenticeship success as just explained is represented by four different dependent variables. First, a dummy variable which indicates whether or not an applicant succeeds in seamlessly entering a certifying firm-based apprenticeship training.[3] Second, a variable for the intellectual standard of the vocational programme the successful applicants follow. Third, a variable that reflects the occurrence of problems during training, and finally, a metric variable that represents the grade in the apprenticeship final examination. The exemplary econometric setting thus looks as follows:

$$Successful\ Transition_i^* \quad = \quad y_i^* = \alpha_i + X_i\beta + B_i^*\pi + \epsilon_i \tag{1}$$

$$Successful\ Transition_i \quad = \quad \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where the vector X stands for students' characteristics that are easily observable at the market and that might be correlated with ability, and B_i^* represents the part of students' ability which is unobservable at first glance.

To test whether hard-to-observe ability influences the transition and training success, we need an ability measure B_i^* that is known to the econometrician and that is correlated with pupils' "true" ability, but at the same time, cannot be easily observed by recruiters of training firms. If B_i^* is correlated with true ability, then its estimated effect $\hat{\pi}$ should significantly differ from Zero if hard-to-observe ability is somehow revealed in the transition process into apprenticeship training. If, however, decisions are only made based on observables, the coefficient $\hat{\pi}$ should not be significant.

A variable that provides us with the possibility to differentiate between observable and unobservable ability is given in our data by a PISA literacy test score. PISA test scores are only observable to researchers, but unknown to teachers, parents, employers, pupils, or any other person or institution. This enables us to create a variable that represents the unobservable

[3] There might be some youngsters who, after unsuccessfully applying for a firm-based apprenticeship, have started some other kind of upper-secondary certifying education, e.g. in fulltime vocational school programmes. These cases are not part of our sample. Furthermore, pupils who stated they want to end up as a nursing professional at the time of the PISA survey (female by the majority) are excluded from the analysis, because, at the time of PISA 2000, the corresponding vocational track for nurses couldn't be started before age 18, which naturally forced the youngsters in interim solutions, internships and non-certifying preparatory courses for at least 2 years.

part of a student's ability, namely the part that is orthogonal to employers' ready-at-hand information. Following the procedure of Farber and Gibbons (1996) we define B_i^* to be the residual from a regression of B_i on all observable students' characteristics X that might act as ability predicting factors. We first regress test scores on the type of school track, school grades and individual background variables such as immigration background, gender, parental education, and other information that is known or assumed to be correlated with school performance and observable to outsiders, either because it is enclosed in school reports or it is common information in letters of application. The unobservable ability part B_i^* can then be obtained by subtracting expected ability (predicted test scores) from observed test scores.

$$B_i^* = B_i - E^*(B_i|X_i) = B_i - X_i\hat{\gamma} \tag{3}$$

The corresponding OLS regression accounts for about 45 percent of the variance in PISA test scores (see model 1c in table 3), showing that many relevant determinants are represented by characteristics that are observable by the market.

We then go one step further and use the residuals B_i^* to create two dummy variables: the first one indicates whether a student belongs to the group of *underachievers*, that is, if actual ability B_i lies to a considerable amount t below the ability level $E^*(B_i|X_i)$ predicted by observable characteristics (negative B_i^* that exceeds a certain threshold), the second one indicates whether someone belongs to the group of *overachievers*, that is, if actual ability lies to a considerable amount t above the level predicted by observable characteristics (positive B_i^* that exceeds a certain threshold). These dummy variables allow us to test whether hard-to-observe ability is revealed, if at all, symmetrically at both ends of the residual distribution.

$$Underachiever_i = \begin{cases} 1 & \text{if } B_i^* < 0 - t \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

$$Overachiever_i = \begin{cases} 1 & \text{if } B_i^* > 0 + t \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

We choose the threshold t to be a value that has some established implication; t equates to the number of score points that lie within the same PISA proficiency level according to OECD (2001) and thus comprises a span of 73 test score points. Therefore, *under*- and *overachievers* are defined to be those students whose realised PISA score differs by more than one proficiency level from what would have been expected according to his/her observable characteristics. Note that the term "-achiever" always refers to the PISA-achievement relative to the expectations throughout the paper.

6. Data and Descriptive Statistics

As a data base we use the Swiss longitudinal data set *Transition from Education into Employment (TREE)* that follows the respondents of the *Programme for International Student Assessment 2000 (PISA 2000)* in their first years after PISA 2000. The TREE survey is based on the national sample of PISA and thus comprises all respondents who were in ninth-grade in year 2000 and therefore in their last year of compulsory schooling[4]. This matched longitudinal data set enables us to observe PISA test scores and individual background characteristics of compulsory school leavers along with detailed information on their further educational and working pathways.

The focus of PISA 2000 was on testing the reading literacy of 15-year-olds in 43 participating countries (OECD, 2001), with mathematical and scientific literacy being investigated incidentally. The average reading literacy test score of Swiss pupils turned out to not significantly deviate from the OECD mean (OECD, 2001), however, there was a comparatively large overall variation in student performance found for Switzerland, combined with a rather strong social selectivity. On a systemic level, this fact seems to be statistically explainable by the high share of (foreign-language) migrants along with an early tracking policy at compulsory school in Switzerland (FSO, 2003).

For the scope of our analysis we do not exploit the rich information of the entire TREE data set.

[4] The Swiss national sample of ninth-graders was added to the PISA study for comparisons between the country's different language regions, as the international PISA survey only covers pupils at age 15, independent of the grade they are in. Because many 15-year-olds are already in the 9th grade, the two populations overlap.

We restrict the sample to those compulsory school graduates who are on the apprenticeship market the year after the PISA test, distinguishing between the successful ones, namely those who follow a firm-based apprenticeship training after compulsory school, and the unsuccessful ones, those who find themselves in some kind of non-certifying interim solution or gap year, albeit they have applied at least once for an apprenticeship place in a firm. This leaves us with 2128 pupils that are observed in PISA as well as one year later. The other outcome variables refer to the sample of those who successfully entered apprenticeship training. As independent variables we only use. besides PISA reading literacy test score results, information on pupils' characteristics that are observable to the labour market and thus might be used by recruiting firms to build expectations about an applicant's ability. Apart from educational credentials, like the type of compulsory school track and school marks, also family background characteristics are expected to play a crucial role in this process, as ability might not be entirely reproduced in school performance indicators.

The school track at lower secondary level is represented by a variable with four categories: *high-level school track* that prepares for high school, *intermediate level school track*, *basic-level school track* (without any requirements) and school track with *no selection*. The share of pupils in different tracks varies between cantons; we thus account for regional variations in educational systems by controlling for *cantons* in all estimations. Further information on the academic performance of a student is given by school marks in annual school reports. These reports are important components of applications for apprenticeships places. The PISA data provides us with information on *school marks in the regional (test-) language*, *mathematics* and *sciences*. All the rest of the used variables provide easy-to-observe information on pupils' individual background. There is information on *gender*, student's *age* (as some of the ninth-graders are one year older due to repetitions of school years) and *migration status*. The latter is represented by two dummy variables, one for *second generation immigrants* (born in Switzerland, but with both parents born outside Switzerland) and one for *first generation immigrants* (students born outside Switzerland). Furthermore, we include information on *highest achieved parental education* (no post-compulsory education, upper secondary level, tertiary level) and *family structure* (nuclear, single, mixed, other). For a complete variable description see definitions in table 1 in Appendix A; for descriptive statistics and bivariate relations to PISA test scores see table 2.

In our study, the PISA reading literacy test score is assumed to meet three important requirements: first, to be observable only to researchers, but not to the market, second, to be correlated with "true" ability and third, to be an objective measure and thus comparable across individuals. Reading literacy is defined in PISA as the ability to *"understand, use and reflect on written texts in order to achieve one's goals, to develop one's knowledge and potential, and to participate effectively in society"* (OECD, 2001, p. 21). It goes far beyond of what is typically tested in schools and is thus expected to have an effect on e.g. labour market success independent of educational attainment.

Initially, the PISA scaling procedure is tuned such that the a posteriori distribution of student competences, with equal weight given to all OECD countries, has mean 500 and standard deviation 100. In our final sample, the average score is 481 (standard deviation 84) ranging from 198 to 813 points.

As discussed in Section 5 we use PISA test scores to create a variable that represents the unobservable part of student's ability, that is, we want to filter out the ability information that is not predictable by observable individual or group characteristics. The results of the corresponding OLS-Regression are presented in table 3 in Appendix B (model 1c).

Figure 1 in Appendix B shows the distribution of the residuals resulting from regressing test scores on students attributes. For 78% of the pupils the regression model is able to predict PISA test scores within the range of one competence level (73 points). 11% of the observations at each end of the residual distribution are identified to be *overachievers* (positive deviation larger than one proficiency level) or *underachievers* (negative deviation larger than one proficiency level). For all these observations, realised test scores of under- and overachievers lie outside the 95% confidence interval of the predicted value.

As for the dependent variables, we first analyse the indicator whether or not somebody who has applied for a training place succeeds in *entering a certifying apprenticeship* directly after compulsory schooling. The share of compulsory school leavers not having an apprenticeship place one year after the PISA test amounts to 28%. These unsuccessful applicants are either enrolled in a non-certifying scholastic interim solution (61%), do an internship or take a gap year e.g. as Au-Pairs (21%) or, finally, are not engaged in any kind of education (18%).

The second dependent variable entails information on the *intellectual aspiration level* of the vocational track for those who have started apprenticeship training. The corresponding aspiration levels for vocational tracks had been rated by experts (vocational advisers) on a scale ranging from 1 to 6.[5]

About 42% of all apprentices in our sample follow an apprenticeship track of high intellectual aspiration level (5 or 6), e.g. towards a certificate as commercial employee, IT-technician, electronic technician, draughtsman, chemist, or optician. About 29% do an apprenticeship of low intellectual aspiration level (1 or 2), as for example hairdresser, gardener, baker, painter, sales person, florist, cook, carpenter, or cosmetician. As shown in table 2 in Appendix A there is a relationship in the data between reading literacy measured by PISA and the intellectual aspiration level of the vocational track someone follows.

In order to test whether hard-to-observe ability further unfolds its effects beyond the transition success, we analyse an indicator that takes value 1 for evidence of problems during apprenticeship training, such as repetition of an apprenticeship year, change of training occupation, failure in the final exam or drop out of training. The share of apprentices who exhibit at least one of those critical events amounts to 16.8% of those, who are observable in the data for the standard duration of their training. Note that we lose some observations due to panel mortality. Finally, as a last measure of apprenticeship success we use the grade in the apprenticeship final examination[6]. Information on final grades ranging from 4 to 6 is available in the sample for those who successfully graduated from apprenticeship training. Failures in the final exams are, amongst others, indicated and analysed within the aforementioned dependent variable.

[5] We have imputed missing information on the aspiration level of some tracks by a regression on training duration and vocational schooling hours (lectures), two factors that strongly explain the aspiration level.

[6] The exam consists of a practical as well as an academic part (general and occupation-specific subjects). The final grade is a weighted average of the marks across different academic subjects (always ranging from 1 to 6) and the practical occupational performance rated by external experts. The latter plays a dominant role insofar as an insufficient mark in the practical exam (below 4) automatically leads to a failure in the overall examination, such that there is no certification and no eligibility for being recognised as skilled worker on the labour market, irrespective of academic excellence.

7. Results

7.1. Probability of directly entering a certifying apprenticeship training

We start by describing the results obtained for the question how observable and hard-to-observe characteristics influence the probability of successfully applying for firm-based apprenticeship training.

In the first probit model in table 4 in Appendix B we only include characteristics that are externally observable and might be used by outsiders to build expectations on students' ability. The estimated marginal effects show that educational signals play a crucial role: Applicants coming from a medium-level compulsory school track have a 8.7 percentage points higher probability of entering apprenticeship training than those from basic-level tracks; the probability of successfully applying at a firm is however highest for those from high-level compulsory schools (by 18.5 percentage points). School marks are important, too, particularly marks in mathematics. Having a mark of 5 (good) instead of 3 (insufficient), increases the probability of immediately starting an apprenticeship by almost 11 percentage points. In contrast, marks in sciences and in the test language (regional language) seem to have no additional effect.

As for the other variables: females, immigrants (first and second generation) and those living in single parent households or patchwork families are less likely to be in certifying apprenticeship one year after PISA, all else equal. On the other hand, having parents with upper-secondary or tertiary education does not significantly increase the probability of having a smooth transition, whereas the coefficients go into the expected direction. Apart from the gender variable and the age 16 dummy, all the coefficients point into the same direction as the coefficients in the PISA test score regression in table 3), indicating that easy-to-observe individual characteristics might indeed play the role of ability predictors in practice.

Model 2 additionally includes the literacy test score as it was measured in the PISA survey. It shows no significant effect on successfully applying for apprenticeship training. The coefficients of the other variables thus are only slightly weakened.

In Model 3 we add the dummy variables of main interest, namely dummies for being either *underachiever* or *overachiever*. Those dummies indicate whether somebody possesses unobserved ability that lies to a considerable amount above/below the expected level predicted by observables. In contrast to Model 2, this allows us to test if hard-to-observe ability components are revealed in a nonlinear way. Since the literacy-information has already been orthogonalised, there is hardly any reaction in the coefficients of the other variables (compared to Model 1). The estimation results show that *underachievers* have a significantly lower probability of 9.4 percentage points of entering certifying apprenticeship compared to someone outwardly identical who performs in the PISA-test as expected. In contrast, an effect for *overachievers* cannot be found. We can thus state the following: two compulsory school graduates with exactly the same individual characteristics with respect to objective school performance and observable family background, have different chances to successfully apply for apprenticeship training - depending on their ability components that cannot easily be observed by outsiders. However, this seems to hold only for the group of underachievers, whereas overachievers do not benefit from potentially being better performers than they are able to signal[7].

As an additional step we split the sample by the level of the compulsory school track, taking together basic-level and no-selection compulsory schooling on the on hand, and the tracks with extended requirements (medium and high-level) on the other hand. The underlying PISA-regressions are presented in table 3 (model 2b and 3b).

According to the results the negative effect of being an *underachiever* is much more pronounced for pupils coming from low-level compulsory school tracks than for higher-level tracks (model 6 and model 9): the probability of having a smooth transition is 21.2 percentage points lower for underachievers of low-level compulsory schooling compared to otherwise identical pupils who achieved as expected in PISA 2000, whereas underachievers coming from compulsory school tracks with extended requirements have a (marginally significant) lower probability of only 7.6 percentage points. This could be interpreted in the way that pre-market screening is more severe for those whose educational signal (compulsory school type) is less favourable from the beginning. Thus, school leavers who can produce evidence of already having successfully passed a sorting process (tracking) at compulsory school might not be screened in a similar thorough way than others. Interestingly, *overachievers* of neither school track are able to

[7] One might argue that, during the hiring process, employers especially look out for noncognitive skills of pupils, for instance their motivation, and that if PISA test scores are correlated with these other factors, our estimations might reflect the importance of these noncognitive factors and not the cognitive abilities, which are already covered by school marks or educational track. We cannot completely rule out such mechanism as they are difficult to test. However, including e.g. the PISA test variable "instrumental motivation" in all our estimations does not alter our results. Although motivation shows significant effects on some of the outcomes, the results regarding our variable describing the hard-to-observe ability component remain unaffected, as there is no correlation between the two independent variables.

realize profits from being smarter than one would expect. Thus, real ability is only decisive as long as it helps to minimize the firm's downward risk.

As for the other variables, the sample split does not reveal additional findings: Being female, immigrant (first or second generation) or coming from non-nuclear families has large significant negative effects on the transition success in both samples, marks in mathematics, however, seem to be more important for those coming from higher compulsory school tracks.

7.2. Intellectual aspiration level of dual vocational track

This section describes the empirical results for the question how hard-to-observe ability components influence the intellectual aspiration level of the apprenticeship track someone enters and thus how it affects the allocation process of sorting young people into different training occupations.

The models 1 to 3 of table 5 in Appendix B contain OLS-results, where the *aspiration level* is a metric dependent variable ranging from 1 to 6. The coefficients of the achiever dummies in model 3 suggest that the part of ability that cannot be predicted by observables unfolds its effect rather symmetrically. *PISA-underachievers* are on average found in lower aspiration levels, *overachievers* are found in higher aspiration levels, both compared to otherwise identical school leavers whose ability is well predicted by easy-to-observe characteristics. Both coefficients are highly significant and more than a half aspiration level in magnitude.

Again, observable characteristics play a crucial role; the effects do not disappear when including PISA test scores in Model 2. The school track followed at compulsory school is again a very decisive factor: those who come from medium-level compulsory schooling are on average found in occupations with a higher rating of 2 aspiration levels, those from high-level compulsory tracks are on average in occupations with higher ratings of 3 levels compared to those coming from low-level compulsory tracks. School marks in mathematics also have a significantly positive effect on the aspiration level. Having for example a mark of 6 (excellent) instead of 3 (insufficient) enables to choose a vocational pathway that is rated almost 1 level higher, all else equal.

In the next models we attempt to allow for different effects at the lower and upper range of aspiration levels. A probit model for the probability to enter a vocational track (training occupation) at *low* intellectual aspiration level (1 or 2) shows significant effects in the expected directions for both hard-to-observe ability dummies (Model 6): there is a slightly significant positive effect for *PISA-underachievers* of 7.9 percentage points and a significant negative effect for *PISA-overachievers* of 13.2 percentage points. Besides, the most important determinants for not being in one of the occupational tracks at low aspiration levels are again given by the level of compulsory school track and school marks in mathematics.

The probit results of models 7 to 9 show marginal effects for the probability of following a vocational track at *high* aspiration level (5 or 6). According to model 9, hard-to-observe ability is again symmetrically revealed in the sense that *underachievers* are significantly less likely to be found in tracks at a high aspiration level (by 20.1 percentage points) and *PISA-overachievers* are more likely to follow a high-aspiration-level track than their identical peers who perform as expected (by 13.9 percentage points). Thus, costly-to-observe ability components play an important role in the allocation process of young people into different training occupations in all estimated models.

7.3. Problems in apprenticeship and grades in final examination

So far we have found that hard-to-observe ability plays a significant role in firms' selection of apprentices. The screening process shows to be accompanied by a sort of pre-market learning, where particularly *negative* ability deviations from predicted group means are detected. It does, however, not imply that ability in either direction is completely revealed in the recruiting process and that learning *after* hiring does not lead to changes in the employer-employee relationship at a later stage.

The longitudinal character of the data allows us to explore the further influence of initially hard-to-observe ability components on outcomes that are related to apprenticeship success. The results of model 3 in table 6 show that hard-to-observe ability significantly affects the probability of facing problems during apprenticeship: *PISA-underachievers* have a 15 percentage points higher probability of either dropping out, repeating a year, changing training occupation or failing the exam; *PISA-overachievers* have a 7 percentage points lower probability of having any problems, both compared to outwardly identical youngsters who achieved in the PISA-test as one would predict. PISA-test-scores and hard-to-observe ability components, respectively, virtually are the only dependent variables that clearly explain the occurrence of problems during apprenticeship training.

Estimations on the grades in the final apprenticeship examination show, again, a rather asymmetric effect: *PISA-underachievers* perform significantly worse than others (model 6 of table 6), *overachievers* do not have significantly better final grades. In contrast to the occurrence of problematic events during apprenticeship, the performance in the final exam is also heavily influenced by the school marks and the school type of compulsory school track. Individual background such as sex and nationality has lost its significance as compared to the probability of finding an apprenticeship place. Easy-to-observe characteristics thus seem to become less important as true ability increasingly reveals itself to the employer in the course of the training.

8. Summary and conclusion

The scope of this paper was to analyse whether and to what extend employer learning about hard-to-observe ability takes place at the very beginning of a worker's career, namely within the transition process from compulsory schooling to marked-based upper-secondary education in Switzerland. In the light of the fact that apprenticeship contracts have standardised contents, fixed duration and leave little scope to adjust prearranged wage profiles over the training period, our first aim was to analyse whether employers successfully try to get further-reaching information on an applicant's ability *before* hiring rather than just relying on ready-at-hand information and thus statistically discriminating on school marks, level of compulsory school track, gender or family background characteristics. Second, we analysed whether hard-to-observe ability gets further revealed in the course of the apprenticeship period and is thus transmitted into observable training outcomes.

Along with variables that reflect easy to get information about an applicant, we use PISA 2000 test scores as an ability measure that is only observable to the researcher, but not observed by recruiters of firms offering training places. We test how deviance in the PISA test scores from what one would predict based on observable characteristics influences the transition and training success. Among those applicants who significantly differ from their predicted group mean in PISA test scores, we technically distinguish between *underachievers* (negative deviation, meaning they are less able than one would predict) and *overachievers* (positive deviation, meaning that they are smarter than one would expect).

Our results suggest that this kind of hard-to-observe ability plays a significant role for the transition as well as the training success, but not always in a symmetric manner.

Regarding applicants' transition success we find that only PISA-underachievers are affected by pre-market employer learning. They are less likely to successfully apply for apprenticeship places than their otherwise identical peers. The negative effect is largest for those underachievers who cannot produce evidence of already having successfully passed a sorting process at compulsory schooling (tracking). Overachievers, in turn, do not seem to benefit from having more academic potential than they are able to demonstrate. Therefore, costly-to-observe ability components are only revealed at the lower end of the residual distribution, indicating that firms invest in pre-market learning particularly in order to minimize the downward risk of a mismatch. Interviews, own screening-tests (so called multi-checks or basic-checks) and trial days are widespread channels through which hard-to-get ability information might reach the employers. We cannot exclude the possibility that hiring decisions are also based on statistical discrimination, as many of the individual attributes as sex, nationality and family background as well as educational credentials show still significant effects after controlling for PISA test scores.

As for the resulting allocation of successful applicants into different intellectually demanding vocational tracks we find, however, rather symmetric hard-to-observe ability effects: PISA-underachievers are found in less intellectually demanding professions than their otherwise identical peers, overachievers are sorted into more demanding apprenticeships than otherwise comparable applicants. Hard-to-get ability information is thus revealed in a way that it significantly increases allocative efficiency at both ends of the distribution.

Summarised, hard-to-observe ability already (partially) unfolds its effects within the transition process into apprenticeship training.

The results regarding long-term outcomes suggest, however, that there is still additional revealing of ability during the subsequent training period. Apprentices who were PISA-overachievers are less likely to face problems such as drop outs, repetition, changing vocational track or final exam failure. In turn, PISA-underachievers, who despite their lower than expected ability successfully found an apprenticeship, are disproportionally more likely to be exposed to these problematic events. Additionally, PISA-underachievers have lower final grades than their otherwise identical peers, whereas there is no significant positive effect for PISA-overachievers. The fact that underachievers who successfully found an apprenticeship show inferior outcomes during the apprenticeship period provides an additional explanation why firms seem to place more emphasis on detecting under- rather than overachievers in the course of the hiring process.

We can show in this paper that in the case of costly and far-ranging hiring decisions, such as apprenticeship training contracts, information that cannot be observed easily is already used by employers at the initial stage of the hiring process and that applicants that differ from their apparently similar peers in regard of their true ability are in consequence treated differently.

References

Acemoglu, Daron and Joern-Steffen Pischke (1998). Why do firms train? Theory and evidence. *Quarterly Journal of Economics 113*(1), 79–119.

Aigner, Dennis J. and Glen G. Cain (1977). Statistical Theories of Discrimination in Labor Markets. *Industrial and Labor Relations Review 30*(2), 175–187.

Altonji, Joseph G. and Charles Pierret (1997). Employer Learning and the Signaling Value of Education. In I.Ohashi and T.Tachibanak (Eds.), *Industrial Relations, Incentives and Employment*, pp. 159–195. London: Macmillan Prese Lt.

Altonji, Joseph G. and Charles R. Pierret (2001). Employer Learning and Statistical Discrimination. *Quarterly Journal of Economics 116*, 313–350.

Arrow, Kenneth J. (1973). The theory of discrimination. In O.Ashenfelter and A.Rees (Eds.), *Labour Markets*. Princeton, NJ.: Princeton University Press.

Bauer, Thomas K. and John P. Haisken-DeNew (2001). Employer learning and the returns to schooling. *Labour Economics 8*(2), 161–180.

Becker, Gary (1957). *The Economics of Discrimination*. Chicago: University of Chicago Press.

Bertschy, Kathrin, M. Alejandra Cattaneo, and Stefan C. Wolter (2009). PISA and the Transition into the Labour Market. *LABOUR: Review of Labour Economics and Industrial Relations 23*(1), 111–137.

Brunello, Giorgio (2009). The effect of economic downturns on apprenticeships and initial workplace training: a review of the evidence. *Empirical Research in Vocational Education and Training 1*(2), 145–171.

Farber, Henry S. and Robert Gibbons (1996). Learning and Wage Dynamics. *The Quarterly Journal of Economics 111*(4), 1007–1047.

FSO (2000). *Statistik der Schülerinnen, Schüler und Studierenden 2000*. Neuchâtel: Federal Statistical Office.

FSO (2003). *Soziale Integration und Leistungsförderung. Thematischer Bericht der Erhebung PISA 2000*. Neuchâtel: Federal Statistical Office.

FSO (2007). *Statistik der Schülerinnen, Schüler und Studierenden - Bildungsperspektiven.* Neuchâtel: Federal Statistical Office.

Galindo-Rueda, Fernando (2003). Employer learning and schooling-related statistical discrimination in Britain. *IZA Discussion Paper no. 778, Institute for the Study of Labor, Bonn.*

Gibbons, Robert and Lawrence F. Katz (1991). Layoffs and Lemons. *Journal of Labor Economics 9*(4), 351–380.

Greenwald, Bruce C. (1986). Adverse selection in the labor market. *Review of Economic Studies 53*(3), 325–347.

Muehlemann, Samuel, Juerg Schweri, Rainer Winkelmann, and Stefan C. Wolter (2007). An Empirical Analysis of the Decision to Train Apprentices. *LABOUR: Review of Labour Economics and Industrial Relations 21*(3), 419–441.

Muehlemann, Samuel, Stefan C. Wolter, and Adrian Wueest (2009). Apprenticeship Training and the Business Cycle. *Empirical Research in Vocational Education and Training 1*(2), 173–186.

OECD (2001). *Knowledge and Skills for Life. First Results from the OECD Programme for International Student Assessment (PISA) 2000*. Paris: OECD.

Phelps, Edmund S. (1972). The Statistical Theory of Racism and Sexism. *The American Economic Review 62*(4), 659–661.

Spence, Michael (1973). Job Market Signalling. *Quarterly Journal of Economics 87*(3), 355–374.

Topel, Robert H. and Michael P. Ward (1992). Job Mobility and the Careers of Young Men. *The Quarterly Journal of Economics 107*(2), 439–479.

Wolter, Stefan C. and Paul Ryan (2010). Apprenticeship. In E.A.Hanushek, S.Machin, and L.Woessmann (Eds.), *Handbook of Economics of Education*, Volume 3, pp. 521–576.

A. Descriptive Statistics

Table 1: Variable Definition

Variable	**Definition**
Certifying education	Dependent variable. Equals 1 if pupil enters a certifying upper-sec. education in form of apprenticeship training directly after compulsory school, 0 otherwise (non-certifying interim solutions or no education).
Aspiration level	Dependent variable. Aspiration level of 105 vocational tracks (expert ratings) from 1 (low) to 6 (high). Used in metric form as well as in form of 2 dummy variables: low aspiration level equals 1 if rating is 1 or 2, 0 otherwise; high aspiration level equals 1 if rating is 5 or 6, 0 otherwise.
Problems in training	Dependent variable. Equals 1 if apprentice exhibits repetition of apprenticeship year, failure in exam, change in training occupation or drop out.
Grade of final exam	Dependent variable. The average grade of the final apprenticeship examination. Metric scale 4 - 6 (4 = sufficient, 6 = excellent).
PISA test score	Reading literacy test score from the PISA 2000 survey.
Underachiever	Equals 1 if PISA test score is considerably (1 competence level) lower than predicted by observables, 0 otherwise.
Overachiever	Equals 1 if PISA test score is considerably (1 competence level) higher than predicted by observables, 0 otherwise.
Female	Equals 1 if female, 0 if male.
Nationality	Dummies representing 3 categories: Swiss (born in Switzerland with at least one parent born in Switzerland), "second generation immigrant" (pupil born in Switzerland but parents born outside Switzerland), "first generation immigrant" (pupil and parents foreign born).
Age 16 at PISA survey	Equals 1 if pupil was age 16 at the time of PISA 2000, 0 if age 15.
Parental education	Dummies representing 3 categories of highest parental education: compulsory school, upper-sec. education, tertiary education.
Family structure	Dummies representing 4 categories: nuclear, single, mixed and other, where the last category also covers missing information.
Mark in test language	Mark in test language (German, French, Italian, depending on linguistic region) in last school report. Metric scale 1-6 (1=lowest, 6=highest).
Mark in mathematics	Mark in mathematics in last school report (1=lowest, 6=highest).
Mark in sciences	Mark in sciences (mean across biology, chemistry, physics, sciences) in last school report. Metric scale 1-6 (1=lowest, 6=highest).
Level compulsory school	Dummies for the school track that was attended at the time of the PISA 2000 survey: low-level compulsory school (e.g. Realschule), medium-level compulsory school (e.g. Sekundarschule), high-level compulsory school (e.g. Pro-Gymnasium) and "no selection" (integrated track, mixed).
Regions (cantons)	Dummies for 22 Swiss cantons (= states).

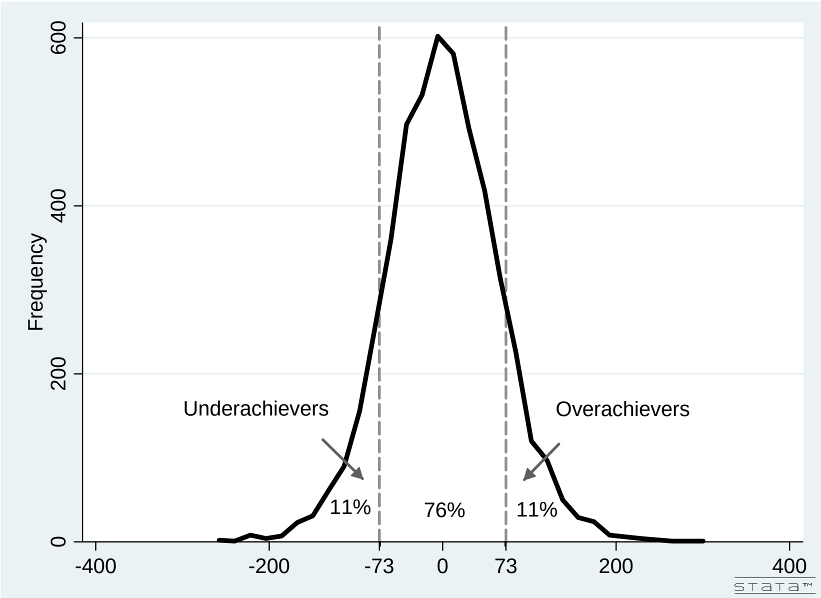
Table 2: Descriptives - univariate and bivariate (with PISA Test Scores)

Continuoues variables (N=2128)	*Mean*	*Std.Dev.*	*Min*	*Max*	*corr PISA*
PISA Literacy test score	480.55	83.93	198.04	812.88	1.00
Mark in test language	4.77	0.65	1.00	6.00	0.24
Mark in mathematics	4.76	0.79	1.00	6.00	0.07
Mark in science	4.95	0.66	1.00	6.00	0.18
Grade of apprenticeship final examination *(N=1125)*	4.81	0.30	4.00	5.90	0.20

		Distribution of PISA Test Scores*			
Categorial variables (N=2128)	*Share (%)*	*Mean**	*Std.Dev.**	*Min**	*Max**
Achieves-as-expected	77.8	480.9	69.2	286.5	643.9
Underachiever	10.9	371.0	61.3	198.0	502.4
Overachiever	11.3	583.4	60.2	444.0	812.9
Male	56.6	475.8	85.1	198.0	737.5
Female	43.4	486.8	82.0	250.6	812.9
Swiss	79.9	494.9	78.5	198.0	812.9
Immigrant: second generation	9.4	439.4	82.5	283.6	622.5
Immigrant: first generation	10.7	410.0	76.8	250.6	634.6
Age 15	65.5	492.2	83.1	198.0	812.9
Age 16	34.5	458.4	81.0	255.0	704.3
Parental education: comp. school	35.3	455.6	83.0	198.0	738.7
Parental education: sec. II	34.3	494.8	83.2	257.7	812.9
Parental education: tertiary	30.4	493.4	79.2	268.1	737.5
Family structure: nuclear	76.6	485.6	83.1	198.0	738.7
Family structure: single	12.4	469.5	76.5	267.1	697.3
Family structure: mixed	6.7	469.0	86.7	257.7	812.9
Family structure: other	4.3	440.0	98.7	255.0	670.5
Track lower sec II: no selection	2.0	457.7	88.3	272.0	676.1
Track lower sec II: low	35.9	421.6	73.5	198.0	653.8
Track lower sec II: medium	47.1	509.6	69.2	294.9	812.9
Track lower sec II: high	14.9	534.1	63.8	357.3	738.7
Educational status one year after PISA (N=2128)					
Certifying apprenticeship training	71.7	488.5	81.3	198.0	737.5
Non-certifying/no education	28.3	460.5	87.3	255.0	812.9
Aspiration level of apprenticeship track (N=1599)					
very low (1)	14.3	442.2	76.9	198.0	640.9
low (2)	14.4	449.5	83.8	278.5	737.4
lower medium (3)	13.9	473.6	71.3	268.8	671.7
upper medium (4)	15.8	474.2	77.5	268.1	670.5
high (5)	8.4	530.3	62.9	323.9	668.7
very high (6)	33.3	527.7	67.9	300.8	737.5
Problems in training (N=1397)					
Any problems (1)	16.8	458.2	74.6	298.3	670.5
No problems (0)	83.1	494.6	81.2	198.0	737.5

B. Figures and Tables

Figure 1: Distribution of unexplained PISA Test Scores (Residuals)



Note: The unexplained part of PISA test scores is computed by subtracting predicted test scores (OLS-regression on all observables) from realised test scores (see section 5 and Model 1c of table 3).
73 Score Points refer to one PISA literacy competence level according to OECD (2001).

Table 3: Estimation results: OLS PISA Literatcy Test-Scores

	OLS Estimation, dependent variable: PISA literacy test-score								
	Sample: All			Sample: compulsory school track without requirements (low-level/no-selection)			Sample: compulsory school track with extended requirements (medium/high-level)		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)
Female		12.211*	7.355+		7.081	6.204		6.125	4.584
		(4.988)	(4.105)		(7.068)	(7.408)		(4.817)	(4.546)
Immigrant: second generation		−46.712**	−25.659**		−31.745**	−27.260**		−28.156**	−25.934*
		(9.279)	(7.282)		(11.159)	(10.447)		(10.774)	(10.170)
Immigrant: first generation		−70.027**	−39.453**		−43.210**	−39.674**		−44.159**	−34.246**
		(8.301)	(6.874)		(8.382)	(8.577)		(11.178)	(10.991)
Age 16		−18.133**	−17.613**		−11.898+	−9.799		−22.662**	−20.209**
		(5.220)	(4.462)		(6.952)	(7.171)		(5.842)	(5.156)
Parental Education: upper sec.		23.243**	8.681+		11.314	5.492		9.760	6.183
		(6.371)	(4.897)		(8.774)	(8.727)		(6.076)	(5.555)
Parental Education: tertiary		21.688**	7.323		14.397+	7.722		8.241	2.899
		(6.620)	(4.944)		(8.278)	(8.108)		(6.398)	(5.868)
Family Structure: single		−10.833+	−4.432		2.108	2.804		−7.477	−12.751*
		(6.508)	(5.947)		(9.433)	(10.427)		(6.422)	(6.351)
Family Structure: mixed		−20.665	−8.568		−18.906	−14.866		−2.787	−1.034
		(13.413)	(10.251)		(19.832)	(19.867)		(8.200)	(8.003)
Family Structure: other		−47.117*	−19.644		−33.280	−23.042		−27.063	−20.599
		(19.100)	(14.335)		(21.529)	(19.308)		(17.922)	(14.758)
School Mark in Test Language	21.341**		18.224**	12.343*		8.719	26.954**		25.993**
	(3.944)		(3.942)	(5.418)		(5.446)	(5.488)		(5.090)
School Mark in Mathematics	6.673*		5.676+	9.694+		8.992	6.497+		4.894+
	(3.097)		(2.998)	(5.631)		(6.029)	(3.320)		(2.902)
School Mark in Sciences	13.414**		10.425**	21.165**		17.090**	9.488*		7.682+
	(3.345)		(3.339)	(5.369)		(5.540)	(4.144)		(3.946)
Track Lower Sec II: no selection	33.174*		23.867	5.777		1.924			
	(14.846)		(14.789)	(14.426)		(14.420)			
Track Lower Sec II: medium-level	88.799**		79.769**						
	(5.206)		(5.126)						
Track Lower Sec II: high-level	139.864**		124.524**				59.796**		55.471**
	(7.147)		(7.067)				(6.730)		(6.676)
Constant	220.442**	483.581**	267.275**	199.073**	416.665**	250.796**	312.244**	520.022**	340.190**
	(23.778)	(6.449)	(23.687)	(38.912)	(12.018)	(39.675)	(28.412)	(9.617)	(26.001)
N	2128	2128	2128	831	831	831	1297	1297	1297
R2	0.403	0.169	0.453	0.256	0.269	0.319	0.219	0.161	0.275

+ $p<0.10$, * $p<0.05$, ** $p<0.01$, robust standard errors in parentheses.
Reference group: male, Swiss parents, age<16, highest parental education: compulsory school, nuclear family structure, low-level compulsory school track in models 1a,1b,2a,2b, medium-level compulsory school track in models 3a,3b.
Cantons are controlled for (22 dummies) in all models.

Table 4: Estimation results: Probabilily of directly entering certifying apprenticeship training

	Probit estimation: 1=direct entry into certifying apprenticeship, 0 otherwise								
	Sample: All			Sample: compulsory school track without requirements (low-level/no-selection)			Sample: compulsory school track with extended requirements (medium/high-level)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PISA Literacy test score		0.000			0.000			0.000	
		(0.000)			(0.000)			(0.000)	
Underachiever			−0.094*			−0.212**			−0.076+
			(0.038)			(0.071)			(0.045)
Overachiever			−0.001			0.001			−0.007
			(0.035)			(0.062)			(0.048)
Female	−0.197**	−0.199**	−0.197**	−0.268**	−0.269**	−0.256**	−0.149**	−0.150**	−0.155**
	(0.023)	(0.022)	(0.022)	(0.037)	(0.036)	(0.035)	(0.026)	(0.026)	(0.026)
Immigrant: second generation	−0.134**	−0.126**	−0.137**	−0.153*	−0.142*	−0.155*	−0.116*	−0.112*	−0.115*
	(0.041)	(0.041)	(0.041)	(0.063)	(0.063)	(0.061)	(0.050)	(0.050)	(0.051)
Immigrant: first generation	−0.166**	−0.154**	−0.168**	−0.190**	−0.173**	−0.194**	−0.128*	−0.123*	−0.128*
	(0.041)	(0.042)	(0.041)	(0.058)	(0.061)	(0.059)	(0.059)	(0.060)	(0.058)
Age 16	0.008	0.013	0.008	−0.018	−0.013	−0.018	0.030	0.032	0.027
	(0.025)	(0.025)	(0.025)	(0.045)	(0.045)	(0.044)	(0.030)	(0.030)	(0.029)
Parental education: upper sec.	0.044	0.042	0.043	0.020	0.019	0.018	0.053	0.052	0.052
	(0.029)	(0.029)	(0.029)	(0.052)	(0.052)	(0.051)	(0.032)	(0.032)	(0.032)
Parental education: tertiary	0.029	0.026	0.029	0.013	0.011	0.016	0.038	0.038	0.039
	(0.030)	(0.030)	(0.030)	(0.053)	(0.053)	(0.051)	(0.034)	(0.034)	(0.034)
Family structure: single	−0.159**	−0.157**	−0.157**	−0.223**	−0.222**	−0.207**	−0.128**	−0.127**	−0.132**
	(0.035)	(0.035)	(0.035)	(0.063)	(0.062)	(0.059)	(0.038)	(0.038)	(0.038)
Family structure: mixed	−0.155**	−0.152**	−0.157**	−0.227**	−0.219**	−0.205**	−0.109*	−0.108*	−0.112*
	(0.042)	(0.041)	(0.041)	(0.067)	(0.063)	(0.060)	(0.051)	(0.051)	(0.051)
Family structure: other	0.044	0.051	0.051	0.023	0.031	0.066	0.074	0.078	0.081
	(0.065)	(0.064)	(0.064)	(0.087)	(0.083)	(0.077)	(0.096)	(0.095)	(0.092)
School mark in test language	−0.004	−0.009	−0.003	−0.018	−0.024	−0.024	0.003	0.000	0.004
	(0.022)	(0.022)	(0.022)	(0.035)	(0.034)	(0.033)	(0.026)	(0.027)	(0.025)
School mark in mathematics	0.053**	0.053**	0.056**	0.037	0.034	0.043	0.056**	0.055**	0.057**
	(0.016)	(0.016)	(0.016)	(0.030)	(0.030)	(0.028)	(0.018)	(0.018)	(0.018)
School mark in sciences	−0.006	−0.009	−0.005	−0.005	−0.012	0.002	0.008	0.007	0.007
	(0.022)	(0.022)	(0.021)	(0.035)	(0.036)	(0.033)	(0.025)	(0.025)	(0.025)
Track lower sec II: no selection	0.022	0.014	0.010	−0.012	−0.011	−0.030			
	(0.093)	(0.093)	(0.093)	(0.103)	(0.103)	(0.102)			
Track lower sec II: medium-level	0.087**	0.064*	0.087**						
	(0.027)	(0.030)	(0.027)						
Track lower sec II: high-level	0.185**	0.152**	0.184**				0.108**	0.101*	0.107**
	(0.045)	(0.050)	(0.045)				(0.041)	(0.043)	(0.041)
N	2128	2128	2128	831	831	831	1297	1297	1297
Pseudo-R2	0.182	0.184	0.187	0.242	0.245	0.259	0.158	0.158	0.161
P(y=1)	0.717	0.716	0.717	0.632	0.632	0.632	0.769	0.769	0.769

+ p<0.10, * p<0.05, ** p<0.01, robust standard errors in parentheses. Average marginal effects are presented.
Reference group: Achieves-as-expected, male, Swiss parents, age<16, highest parental education: compulsory school, nuclear family structure, low-level compulsory school track in models 1-6, medium-level compulsory school track in models 7-9.
Cantons are controlled for (22 dummies) in all models.

Table 5: Estimation results: Intellectual aspiration level of vocational track

	OLS aspiration level: continoeus (1-6)			Probit low aspiration level: 1=low (1 2), 0=otherwise (3 4 5 6)			Probit high aspiration level: 1=high (5 6), 0=otherwise (1 2 3 4)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PISA Literacy test score		0.005**			−0.001**			0.001**	
		(0.001)			(0.000)			(0.000)	
Underachiever			−0.680**			0.079+			−0.201**
			(0.190)			(0.044)			(0.056)
Overachiever			0.539**			−0.132**			0.139**
			(0.123)			(0.044)			(0.037)
Female	0.037	−0.024	−0.002	0.038	0.051+	0.045	0.099**	0.085**	0.090**
	(0.116)	(0.114)	(0.113)	(0.029)	(0.029)	(0.028)	(0.028)	(0.027)	(0.027)
Immigrant: second generation	0.714**	0.811**	0.647**	−0.075	−0.089+	−0.062	0.228**	0.252**	0.207**
	(0.202)	(0.192)	(0.192)	(0.054)	(0.052)	(0.052)	(0.051)	(0.047)	(0.047)
Immigrant: first generation	0.120	0.283	0.125	−0.010	−0.040	−0.012	−0.013	0.025	−0.020
	(0.221)	(0.211)	(0.218)	(0.050)	(0.050)	(0.050)	(0.055)	(0.054)	(0.054)
Age 16	−0.064	0.031	−0.069	−0.001	−0.016	−0.000	−0.011	0.020	−0.008
	(0.121)	(0.118)	(0.120)	(0.031)	(0.030)	(0.030)	(0.031)	(0.030)	(0.031)
Parental education: upper sec.	0.457**	0.417**	0.420**	−0.041	−0.035	−0.033	0.133**	0.117**	0.117**
	(0.145)	(0.142)	(0.141)	(0.035)	(0.034)	(0.034)	(0.033)	(0.032)	(0.032)
Parental education: tertiary	0.215	0.178	0.197	−0.037	−0.029	−0.029	0.057	0.048	0.056
	(0.144)	(0.143)	(0.143)	(0.036)	(0.036)	(0.036)	(0.036)	(0.035)	(0.035)
Family structure: single	0.190	0.181	0.155	−0.004	−0.002	0.004	0.032	0.031	0.028
	(0.161)	(0.161)	(0.159)	(0.046)	(0.045)	(0.045)	(0.046)	(0.044)	(0.044)
Family structure: mixed	−0.174	−0.204	−0.289	0.032	0.044	0.055	−0.023	−0.026	−0.044
	(0.205)	(0.208)	(0.201)	(0.051)	(0.050)	(0.050)	(0.050)	(0.049)	(0.048)
Family structure: other	−0.047	0.016	−0.090	−0.015	−0.027	0.000	−0.045	−0.019	−0.056
	(0.267)	(0.271)	(0.258)	(0.087)	(0.086)	(0.083)	(0.080)	(0.086)	(0.083)
School mark in test language	0.239*	0.147	0.224*	−0.028	−0.016	−0.030	0.108**	0.073*	0.094**
	(0.105)	(0.106)	(0.109)	(0.028)	(0.028)	(0.028)	(0.029)	(0.030)	(0.031)
School mark in mathematics	0.258**	0.226**	0.257**	−0.064**	−0.059**	−0.064**	0.053**	0.048*	0.055**
	(0.084)	(0.082)	(0.082)	(0.022)	(0.022)	(0.022)	(0.021)	(0.020)	(0.020)
School mark in sciences	0.034	−0.013	0.026	−0.012	−0.004	−0.010	0.022	0.011	0.021
	(0.079)	(0.078)	(0.077)	(0.024)	(0.023)	(0.023)	(0.022)	(0.021)	(0.022)
Track lower sec II: no selection	0.275	0.179	0.224	−0.109	−0.091	−0.105	−0.023	−0.040	−0.034
	(0.439)	(0.407)	(0.409)	(0.103)	(0.097)	(0.098)	(0.108)	(0.096)	(0.099)
Track lower sec II: medium-level	1.851**	1.512**	1.886**	−0.303**	−0.247**	−0.311**	0.427**	0.333**	0.433**
	(0.139)	(0.153)	(0.136)	(0.028)	(0.032)	(0.027)	(0.034)	(0.039)	(0.033)
Track lower sec II: high-level	2.897**	2.321**	2.868**	−0.565**	−0.470**	−0.567**	0.682**	0.519**	0.665**
	(0.180)	(0.212)	(0.175)	(0.052)	(0.057)	(0.051)	(0.045)	(0.053)	(0.042)
Constant	0.084	−1.040	0.256						
	(0.645)	(0.659)	(0.632)						
N	1599	1599	1599	1599	1599	1599	1599	1599	1599
R-squared/Pseudo R-squared	0.349	0.370	0.371	0.229	0.241	0.242	0.286	0.313	0.314
P(y=1)				0.286	0.286	0.286	0.417	0.417	0.416

+ p<0.10, * p<0.05, ** p<0.01, robust standard errors in parentheses. Average marginal effects are presented.
Reference group: Achieves-as-expected, male, Swiss parents, age<16, highest parental education: compulsory school, nuclear family structure, low-level compulsory school track.
Cantons are controlled for (22 dummies) in all models.

Table 6: Estimation results: Problems in apprenticeship and grades in final examination

	Probit: Problems in apprenticeship			OLS: Final grade in apprenticeship exam		
	(1)	(2)	(3)	(4)	(5)	(6)
PISA Literacy test score		−0.001**			0.001**	
		(0.000)			(0.000)	
Underachiever			0.150**			−0.093*
			(0.047)			(0.038)
Overachiever			−0.073*			−0.003
			(0.033)			(0.034)
Female	−0.028	−0.023	−0.025	−0.024	−0.029	−0.025
	(0.028)	(0.028)	(0.028)	(0.024)	(0.024)	(0.024)
Immigrant: second generation	0.065	0.035	0.065	−0.034	−0.021	−0.039
	(0.046)	(0.046)	(0.044)	(0.045)	(0.047)	(0.045)
Immigrant: first generation	0.058	0.033	0.056	−0.039	−0.023	−0.034
	(0.049)	(0.050)	(0.049)	(0.043)	(0.045)	(0.044)
Age 16	0.070*	0.051+	0.070*	−0.022	−0.009	−0.023
	(0.031)	(0.029)	(0.029)	(0.025)	(0.025)	(0.025)
Parental education: upper sec.	−0.048	−0.040	−0.039	0.017	0.013	0.016
	(0.033)	(0.032)	(0.032)	(0.026)	(0.026)	(0.027)
Parental education: tertiary	−0.003	−0.004	−0.007	−0.013	−0.018	−0.012
	(0.035)	(0.034)	(0.034)	(0.027)	(0.027)	(0.027)
Family structure: single	0.068+	0.072+	0.076+	−0.063+	−0.071*	−0.066+
	(0.040)	(0.040)	(0.040)	(0.036)	(0.036)	(0.036)
Family structure: mixed	0.024	0.032	0.048	−0.114*	−0.109*	−0.121*
	(0.046)	(0.043)	(0.044)	(0.054)	(0.053)	(0.054)
Family structure: other	0.125	0.119	0.140+	−0.047	−0.041	−0.049
	(0.077)	(0.073)	(0.076)	(0.053)	(0.053)	(0.053)
School mark in test language	0.011	0.031	0.018	0.051*	0.039+	0.048*
	(0.029)	(0.025)	(0.024)	(0.023)	(0.023)	(0.023)
School mark in mathematics	0.008	0.009	0.007	0.043**	0.041**	0.042**
	(0.017)	(0.017)	(0.017)	(0.015)	(0.015)	(0.015)
School mark in sciences	−0.042+	−0.035	−0.044*	0.049*	0.044*	0.050**
	(0.022)	(0.022)	(0.022)	(0.019)	(0.019)	(0.019)
Track lower sec II: no selection	0.069	0.081	0.081	−0.270+	−0.279+	−0.272+
	(0.082)	(0.084)	(0.082)	(0.154)	(0.151)	(0.154)
Track lower sec II: medium-level	−0.006	0.042	−0.025	0.115**	0.072*	0.116**
	(0.036)	(0.039)	(0.036)	(0.032)	(0.033)	(0.032)
Track lower sec II: high-level	−0.050	0.029	−0.066	0.242**	0.182**	0.241**
	(0.050)	(0.052)	(0.050)	(0.045)	(0.047)	(0.046)
Aspiration level 2	−0.029	−0.013	−0.010	0.034	0.022	0.024
	(0.057)	(0.057)	(0.057)	(0.042)	(0.042)	(0.042)
Aspiration level 3	0.059	0.066	0.058	0.067	0.054	0.063
	(0.052)	(0.052)	(0.052)	(0.041)	(0.040)	(0.041)
Aspiration level 4	0.020	0.031	0.025	−0.008	−0.026	−0.014
	(0.051)	(0.050)	(0.049)	(0.044)	(0.043)	(0.044)
Aspiration level 5	0.035	0.076	0.070	−0.067	−0.095*	−0.077+
	(0.056)	(0.057)	(0.057)	(0.043)	(0.045)	(0.044)
Aspiration level 6	0.024	0.057	0.054	−0.144**	−0.167**	−0.154**
	(0.047)	(0.048)	(0.047)	(0.036)	(0.037)	(0.037)
Problems in apprenticeship				−0.026	−0.017	−0.018
				(0.032)	(0.033)	(0.033)
Constant				4.088**	3.932**	4.110**
				(0.146)	(0.153)	(0.146)
N	1397	1397	1397	1125	1125	1125
R2/Pseudo-R2	0.1217	0.142	0.145	0.185	0.197	0.190

+ p<0.10, * p<0.05, ** p<0.01, robust standard errors in parentheses. Average marginal effects presented. Ref. group: Achieves-as-expected, male, Swiss parents, age<16, highest parental education: comp. school, nuclear family, low-level comp. school track. Cantons are controlled for (22 dummies) in all models.