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The consequences of being different - Statistical discrimination and the school-to-work transition

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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. It is therefore interesting to know, by how much employers rely on easily observable characteristics and by how much they are influenced by hard to get information in their actions. 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 the probability to get an apprenticeship contract in a profession with higher intellectual demand. Our results suggest that hard-to-get information plays a significant role in the transition, but in an asymmetric manner. Underachievers, students with test-scores significantly below their predicted group mean, face disadvantages in the transition, whereas overachievers do not seem to realize profit from their positive deviation.

JEL classification: I2, J24, J71

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, sex, race or other readily-available factors that are assumed to be correlated with the lacking information (Spence, 1973; Phelps, 1972; Arrow, 1973; Aigner and Cain, 1977). The statistical discrimination literature has been enhanced by the dynamic component of employer learning models wherein workers' true productivity is gradually revealed over time. Farber and Gibbons (1996) and Altonji and Pierret (2001) empirically test this idea and use Armed Forces Qualification Test-scores (AFQT) as information that is known to the econometrician but hard to observe for an employer. They find that the influence of these variables on wages increases with workers' experience, which shows that employers learn about workers' ability and adjust wages accordingly. At the same time, Altonji and Pierret (2001) find that the effects of easily observed variables fall over time.

In this paper we want to investigate whether and to what extend learning about ability takes place even before the start of a workers' career, namely within the transition process from compulsory schooling to marked-based upper-secondary education in Switzerland. Due to the predominant firm-based vocational system, a large part of post-compulsory schooling entails early integration (age 16) into the labour market and is therefore prone to market forces. Firms' and educational institutions' screening devices naturally play an important role within the sorting process of youngsters into different vocational and academic tracks. We therefore ask the question whether the success in the transition from compulsory school to upper-secondary firm-based education solely depends on the attractiveness of a pupil's signals or whether, alternatively, students' true ability is partly revealed and taken into account.

This topic is of utmost political relevance: not only are there claims that firms generally show insufficient willingness to hire apprentices and thus force a considerable part of compulsory-school graduates every year into (sometimes expensive) non-certifying scholastic interim solutions, but also are there signs that the process of allocation of training places might discriminate pupils with unfavourable attributes such as 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 firms may base their decisions on easily observable characteristics. Firstly, many of individual background characteristics are indeed correlated with true school performance, and secondly, firms are reluctant to rely on school marks 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 a poor predictor of the true ability of an applicant. It is therefore only naturally to assume that firms build expectations based on all easy to observe ability proxies and decide accordingly. However, in the Swiss educational system with its early tracking policy (age 12) on lower secondary level and the strong relationship between tracking outcome and individual family background characteristics, the sorting mechanism prior to the transition into upper-secondary education might already predetermine the options, partly independent of pupils' actual performance. Not only in terms of equity, but also in terms of allocative efficiency the effective achievement potential of a student rather than his family background should act as a decisive determinant for his/her educational career prospects. Reversed, if only background characteristics, not scholastic deficits, force young people into non-certifying interim-solutions, the system could hardly be perceived to be efficient or fair.

In order to test whether hard-to-observe students' ability is revealed and accounted for within the transition from schooling to mostly market-based education, 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 or educational establishments. 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. 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 is revealed in favour of those students who appear to be less able

[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).

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. The empirical strategy is described in section 4. Section 5 presents the data and descriptive statistics, the results are discussed in section 6. Finally, Section 7 concludes with a summary and discussion of our findings.

2 Swiss education system and the transition into upper secondary levels

2.1 Swiss education system

Compulsory school in Switzerland comprises 9 school years: about 6 years of primary school and 3 years of lower secondary school. There is variation between cantons (districts) with respect to the design of school type models: normally, there is a selection at lower secondary level into different school tracks according to pupils' intellectual ability, teachers' recommendations and parental decisions. In the majority of cantonal school systems there exist three possible tracks: an upper-level school track (*Pro-* or *Untergymnasium*) which is the most intellectually demanding one and enables direct entry into High School (Gymnasium), an intermediate level track (e.g. *Sekundarschule*), and finally a track offering basic-level courses (e.g. *Realschule*). There is considerable variation between cantons in the quantitative importance of these different school tracks, which implies that the respective ability thresholds vary, too.

After 9 years of compulsory schooling the majority of a cohort typically follows a dual apprenticeship training that lasts 3 to 4 years, depending on the training occupation. Apprentices are most likely to come from the intermediate and basic compulsory school track. This form of education at upper secondary level 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). Apprenticeship trainings lead to a nationally recognised certificate, where compulsory content, length of training and type of certificate are regulated by federal laws for every single of about 250 professions. These kinds of vocational tracks are also attractive for pupils with high cognitive abilities since apprenticeships can be combined with a professional baccalaureate (*Berufsmatur*) that allows direct enrolment in tertiary studies at the Universities of Applied Sciences (Tertiary A level).

Apart from firm-based (dual) 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). In order to get a professional baccalaureate within a full-time vocational path, professional experience of several months is demanded. This kind of work experience is usually acquired in the form of internships after graduation.

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[2] 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 enrolled in a high school programme (Gymnasium), which normally lasts between 3 and 4 years and provides direct access to academic universities. High school 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. Apparently, the high-school graduation rate of Switzerland is rather low compared to other OECD countries, even if it shows an increasing pattern over the past decades from 10.6% in 1980 to 19.7% in 2008 (FSO, 2009).

The structurally low high-school graduation rate of Switzerland implies that a considerable part of the population with high intellectual ability choose to pursue a vocational alternative.

[2] We follow the calculation of Schweri and Mueller (2008), where only those entries into certifying education pathways are counted that normally belong to the group of degrees that are first-time qualifications.

This is also highlighted by the fact that, despite the low share of students following a general education track, the overall graduation rate in tertiary education amounts to 50% and is thus slightly above OCED average (OECD, 2009). This share mainly results from the fact that vocational education diplomas generally provide access to further professional degrees at the tertiary B level and, in combination with a professional baccalaureate (*Berufsmaturität*), to the tertiary A level (universities of applied sciences).

Further, the associated returns on education of apprenticeships are similar to those for young people attending a high-school, and the returns on education of universities of applied sciences are considerably larger than those of universities (Weber et al., 2001).

2.2 Vocational education and transitions

As noted above, about two thirds of a cohort enter a dual apprenticeship programme that consist of vocational schooling and firm-based training. Upper-secondary education of a considerable part of compulsory school leavers is thus prone to market forces: dual apprenticeship trainings require a contract with a training firm. Besides business cycle effects, that generally tend to affect 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 and succeeds in successfully integrating a vast majority of pupils into post-compulsory education, and later on, into the labour market. Similar to other countries with predominant apprenticeship systems, youth unemployment rates are rather low in Switzerland compared to the OECD average (OECD, 2000). The increasing high school graduation rate and thus the on average lower expected ability of youth applying for apprenticeships did not lead to a similar decrease in the significance of vocational education.

Besides the increased demand on the integrating function of the vocational education and training (VET) system there is, at the same time, ongoing technological change and a shift towards a larger service industry, presumably leading to increased requirements on workers' qualifications, educational prerequisites and social competences. Maybe as a consequence, the transition from compulsory school to vocational education is observed to be less smooth nowadays; there are concerns that finding an apprenticeship place is getting 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.

There is evidence that finding an apprenticeship place is not equally difficult for different groups of school leavers. Immigrants for example have to apply more times than Swiss pupils (Link, 2009), the same is true for females; however, it does not emerge out of the data if they applied for comparable apprenticeships.

However, screening on e.g. school-track and school marks cannot be expected to do full justice to someone's actual performance potential. First, the outcome of the selection process into different aspiration levels at compulsory school depends on the regional (cantonal) educational system and local school facilities, and moreover, is already strongly related to family background characteristics and parental aspirations. Second, school marks only provide information on relative performance within a peer group and depend on a single teachers' rating.

3 Related Literature

Recruiters of firms and educational institutions only have limited information about the true skills of a compulsory school leaver. They might try to obtain better information by e.g. own screening tests, but only as long as it is worth the costs. In this case, 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). As inexpensive to observe characteristics might act information on educational credentials, sex, race, age, school quality, and so on. Statistical discrimination is the solution to a signal extraction problem: given that there is a signal for a worker's productivity (e.g. educational credentials) and the signal is only believed to be a proxy, then more accuracy in predicting someone's ability can be gained by considering also group memberships as gender or race, as long as they provide additional information due to different group specific (expected) mean productivities. Additionally, if the signal is believed to be less reliable for one group, then less weight will be put on the signal for this group and more weight on the expected group mean performance (Aigner and Cain, 1977).

Statistical discrimination can be seen as an efficiency enhancing strategy in case of lacking information. Whereas it is discriminating on the individual level (unequal treatment of equal able individuals), it is not discriminating on average: there is equal treatment of individuals with equal expected ability[3].

However, the presence of asymmetric information on worker's ability and thus the importance of educational signals in firms' screening procedure might in turn have a feedbacks on believes and the behaviour of actors: as proposed by Spence (1973), higher ability individuals will signal themselves as such by investing more in education (the signal), as this is less costly for them due to a higher capacity of learning. In turn, firms might build up screening mechanism to encourage workers' self-selection and the revealing of accurate information Stiglitz (1975). Statistical discrimination can be self-confirming (Arrow, 1973; Lundberg and Startz, 1983; Coate and Loury, 1993). If employers are going to judge e.g. by race, then there is no (or less) reward for the investment in education for minority groups and it will thus not be acquired; as a result, the statistical judgements will be confirmed.

[3] This must, however, no longer be the case in the presence of employers' risk aversion (Aigner and Cain, 1977)

Statistical discrimination is empirically difficult to test, as a significant coefficient of the race or gender variable could also reflect taste based discrimination as it was formulated in Becker (1957). To distinguish between the two concepts, a measure of individuals' productivity is needed. A measure assumed to be correlated with someone's ability that is observable to the econometrician but not to the market was found in the US Armed Forces Qualification Test-scores (AFQT) of the National Longitudinal Survey of Youth 1979 (NLSY79).

Farber and Gibbons (1996) formalised an employer learning model and used the AFQT-variable to test whether information on someone's ability is revealed over time in the labour market. They find that the part of test score information that was not predictable by statistical discrimination at market entry becomes increasingly correlated with wages as market experience increases. Altonji and Pierret (1997, 2001) are building upon Farber and Gibbons' work. Without orthogonalising the residuals they build up a framework to simultaneously investigate employer learning and statistical discrimination. They find that wages not only become more dependent on a worker's ability (measured by AFQT-tests), but at the same time also become less dependent on easily observable characteristics. The latter result can be seen as evidence that firms initially form believes about the productivity of a worker by statistical discrimination e.g. on educational credentials and race, and then, as time goes by and more information is available, revise believes accordingly. The results suggest that firms learn quickly enough to limit the signalling value of education: the 'signalling component' of the return to education is shown to be probably only small (see also Lange, 2007). 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).

The focus of all these studies is on symmetric employer learning, that is, all firms in the market learn simultaneously about workers' ability. If, however, current employers get better informed about the abilities of their workers (asymmetric learning) compared to potential employers, employees' wages and mobility will be affected (Greenwald, 1986; Gibbons and Katz, 1991); firm movers are then expected to belong to an adverse selected group, private knowledge of the incumbent firm provides them with monopsony power. Schoenberg (2007) builds open this literature and develops a model to test whether learning of incumbent and recruiting firms happens symmetrically or asymmetrically. Using the same data as Farber and Gibbons (1996) and Altonji and Pierret (1997, 2001) she finds that learning about cognitive ability appears to

be largely symmetrically: there is little evidence that workers who leave firms are negatively selected; furthermore, the effect of AFQT test scores increases with experience but not with tenure, the impact of schooling decreases with experience but changes little with tenure.

Considering the far reaching hiring decision of offering an apprenticeship contract to a 16-year-old and thus committing to a standardised amount of training in a certain occupational field with a duration of three to four years, the question arises whether firms indeed are willing to take a large amount of uncertainty about a trainee's ability. If they do so, the potential for employer learning would be large. But unlike other labour markets, in market-based vocational education systems the sorting process of young school leavers into firms and occupations is normally not based on trial and error (job shopping)[4], nor is there much scope for firms to adjust training wages or the standardised content or length of training.

In addition, drop outs due to a bad match between trainee and e.g. the aspiration level of the apprenticeship track are costly for both apprentices and training firms: the trainee incurs costs of forgone time and earnings (as well as psychical costs and probably stigmatisation), the training firm incurs stranded costs, since training investments mostly exceed the productive contribution of an apprentice during the first years of an apprenticeship. Therefore, one would expect that firms try do minimize the risk and do not entirely base their hiring decision on statistical discrimination and stereotyping (as it is sometimes feared), but that they considerably invest in pre-screening via reference letters, screening-tests, interviews and trial days (*"Schnupperlehren"*) in order to reduce uncertainty about the ability of the applicant prior to the contract.

The scope of this paper is to test whether someone's ability gets partly revealed within the process of transition into upper-secondary education.

[4] Which stands in contrast to the US labour market where "job shopping" is an important driving force behind the sorting process of youngsters in firms and occupations where they are most productive (Topel and Ward, 1992)

4 Empirical Strategy

We want to empirically test whether the success at the transition from compulsory school to certifying upper-secondary education is exclusively based on *observable* students' characteristics such as educational signals and individual background, or whether students' ability is revealed and accounted for within the transition process.

Our analysis is performed using two different dependent variables for transition success: first, a dummy variable which indicates whether or not someone succeeds in seamlessly entering a certifying education, be it a vocational training programme or a general education track, and second, a variable that indicates whether someone who enters a dual vocational track follows a high- or low-intellectual standards apprenticeship programme. The 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 perform our test, 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 or educational establishments. If B_i^* is correlated with ability, then its estimated effect $\hat{\pi}$ should significantly differ from Zero if hard-to-observe ability is somehow revealed in the transition process from school to certifying education. 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. It enables us to create a variable that represents the unobservable part of a student's ability, namely the part that is

orthogonal to employers' and other recruiters' 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, sex, parental education, and other information that is known 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 40 percent of the variance in PISA Test Scores (see model 0 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 level), 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 level). These dummy variables allow us to test whether hard-to-observe ability is revealed, if at all, symmetrically at both ends of the 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.

5 Data and Descriptive Statistics

We use the Swiss national sample from the *Programme for International Student Assessment 2000 (PISA 2000)* and the longitudinal data set *Transition from Education into Employment (TREE)* that follows the respondents in their first years after PISA 2000 (see TREE, 2008). 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 TREE data covers all ninth-graders (pupils in their last year of compulsory school) of the PISA survey 2000. The national sample of ninth-graders was added to the PISA study, as the international PISA survey only covers pupils at age 15, independent of the grade they are in.

PISA 2000 focused on testing the reading literacy of 15-year-olds in 43 participating countries (OECD, 2001). The average test score in reading literacy of Swiss pupils does not significantly deviate from the OECD mean (OECD, 2001; FSO, 2002), but there is comparatively large overall variation in student performance, with a higher-than-average share of pupils who do not entirely succeed in understanding simple messages in texts. Social selectivity has been found to be rather strong in Switzerland: there are large effects of family background characteristics on the PISA test score. On a systemic level, this is entirely statistically explained by a high share of (foreign-language) migrants along with the early tracking policy at compulsory school (FSO, 2003).

Out of the wide range of variables in the TREE data we use PISA test scores along with all information on pupils' characteristics that are observable to recruiters of educational institutions and firms and that might be used to build expectations about a student's ability. Apart

from educational credentials as the type of compulsory school track and school marks, there are family background characteristics that are expected to play a crucial role, if ability is not believed to be entirely reproduced in school performance indicators.

The school track at lower secondary level is represented in our data by a variable with three categories: *high-level school track* that prepares for high school, *intermediate level school track* and *basic-level school track*. The share of pupils in different tracks varies between cantons. To account for regional variations in educational systems and the composition of the population we therefore control for *cantons* in all estimations. Further, given the school track, more information about the academic performance of a student is gained by school marks as enclosed in the school report at the end of the school year. School reports are important components of applications for apprenticeships and schools. The PISA data provides us with information on *marks in test-language*, *mathematics* and *sciences*. Important individual characteristics are *sex*, student's *age* (as some of the ninth-graders are one year older due to repetitions of school years) and *migration background*. 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). Further, there is information on *highest achieved parental education* (no post-compulsory education, upper secondary level, tertiary level) and *family structure* (nuclear, single, mixed, other). Finally, we include a school variable that accounts for the share of migrants at the school (own calculations with PISA data) as a proxy for e.g. local reputation. To perform our analysis we drop those students who followed a high-level compulsory school track that provides direct access and seamless transitions to high-school programmes; this part of compulsory school leavers does not belong to the population we are interested in. This leaves us with 2725 pupils that are observed in PISA and are in our sample.

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 494 (standard deviation 80.5) ranging from 198 to 813 points.

As discussed in Section 4 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 the first column of table 3 in Appendix B.

Figure 1 in Appendix B shows the distribution of the residuals resulting from regressing test scores on students attributes. For 76% of the pupils the regression model is able to predict PISA test scores within the range of cone competence level (73 points). 12% 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). We additionally tested whether realised test scores of under- and overachievers lie outside the 95% confidence interval of the predicted value. This was the case for all observations.

In order to test whether *underachievers* and *overachievers* are detected within the transition process from compulsory school to certifying education and thus within one year after the PISA 2000 survey, we use two different dependent variables. First, we analyse an indicator whether or not somebody succeeds in *directly entering a certifying upper-secondary education.* The share of (low- and medium-level) compulsory school leavers who, potentially involuntarily, are not in certifying education one year after PISA, amounts to 29%. They are either enrolled in a scholastic interim solution (64%), do an internship or take a gap year e.g. as Au-Pairs (24%) or, finally, are not engaged in any kind of education (12%).

The second part of our analysis is restricted to those who have started apprenticeship training and for whom the aspiration level of the vocational track is known (1167 observations). The corresponding dependent variable thus reflects information on the *aspiration level of the dual vocational track.* The intellectual aspiration level of vocational tracks had been rated by

experts (vocational advisers) on a scale ranging from 1 to 6 (see Bertschy et al., 2009, for the importance of the aspiration level of the vocational track in the apprenticeship-to-work transition). About 40% of all apprentices in our sample do an apprenticeship track of high intellectual aspiration level (5/6); corresponding training occupations are commercial employee, IT-technician, electronic technician, draughtsman, chemist, or optician. About 30% do an apprenticeship of low intellectual aspiration level (1/2), 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.

6 Results

6.1 Probability of directly entering a certifying upper-secondary education

In the first model in table 3 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 of the Probit model show that educational signals play a crucial role: Pupils coming from a medium-level compulsory school track have a 14 percentage points higher probability of directly entering a certifying education than those from a low-level (basic-level) compulsory school track. School marks are important, too, particularly marks in mathematics. Having a mark of 5 (good) instead of 3 (insufficient), increases the probability of entering a certifying education by almost 14 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, first generation (but not second generation) immigrants and those living in single parent households or patchwork families are less likely to be in certifying education 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, all the coefficients point into the same direction as the coefficients in the PISA test score regression of Model 0, indicating that easy-to-observe individual characteristics

might indeed play the role of ability predictors in practice, beyond educational signals.

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

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 7.5 percentage points lower probability of entering certifying education than someone outwardly identical who performs as expected. In contrast, an effect for *overachievers* cannot be found. We can thus state the following: two compulsory school graduates, who are showing exactly the same individual characteristics with respect to objectified school performance and family background, indeed have different chances to enter directly a certifying education - depending on their ability components that cannot easily be observed by outsiders. However, this only seems to hold for one group: underachievers are revealed as such, whereas overachievers do not benefit from potentially being better performers than they are able to signal.

As a next step, we split the sample by the level of the compulsory school track. As only a few school leavers come from an integrated track where no selection took place at the age of 12, we focus on low- and medium-level school track graduates. The previous results with respect to under- and overachievers are reinforced when only looking at those coming from basic-level courses (Model 6): *underachievers* have 12.1 percentage points lower probability of having a smooth transition, that is, they are revealed as such in the process of pre-market screening. Further, the negative coefficients of being female, immigrant (first or second generation), or coming from non-nuclear families is now larger in absolute terms compared to the pooled model. There is no effect of the PISA test scores (Model 5), which, as it suggests itself, is due to the highly asymmetrical effect of hard-to observe ability and therefore the fact, that *overachievers* are not revealed as such at all.

In contrast to the discussed results for school leavers from low-level compulsory tracks, none

of the achiever dummies shows a significant effect in the sample of *medium-level compulsory school* leavers (Model 9). The findings suggest the following: school leavers who produce evidence of already having passed a sorting process (tracking) at compulsory school, are not screened in a similar thorough way than those of the basic-level compulsory track. Independently of being less able (by more than one PISA proficiency level) than their outwardly identical peers, *underachievers* of medium-level tracks are *not* more likely to end up in interim solutions and gap years[5]. Especially for immigrants, the value of having followed a track with extended requirements seems to prevent them from having less chances to enter post-compulsory education, ceteris paribus: the influence of being first (or second) generation immigrant has disappeared. The same doesn't hold for females, however, which is not easy to explain but is consistent with data of official statistics[6].

6.2 Intellectual aspiration level of dual vocational track

For the next estimations we restricted the sample to those who entered firm-based apprenticeship training and for whom we know the intellectual aspiration level of the vocational track. The question we want to investigate here is whether hard-to-observe ability is somehow revealed within the sorting process into different training occupations, which for example vary considerably with respect to training duration and the time spent at vocational school. The models 1 to 3 of table 4 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. *Underachievers* are on average found in lower aspiration levels, *overachievers* in higher aspiration levels, both compared to otherwise identical school leavers whose ability is well predicted by easy-to-observe characteristics; the effect for overachievers is, however, only slightly significant.

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

[5] The results remain unchanged if we estimate PISA-models *separately* for school leavers of low- and medium-level compulsory school tracks.

[6] This result remains unchanged when we exclude those pupils (female by the majority) who whished to end up as a nursing professional at the time of the PISA survey. At this time, the corresponding vocational track 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.

a very decisive factor: those who come from compulsory school with extended requirements (medium-level track) are on average found in occupations that are rated higher by 2 levels. The mark in mathematics also has a significant positive effect on the aspiration level. Having for example a mark of 6 (very good) instead of 3 (insufficient) enables to choose a vocational pathway that is rated almost 1 level higher, all else equal. The school mark in the language of the region is also significant and has a similarly strong effect. Highest parental education has an influence, too; the effect is, however, only significant for those whose parents have upper-secondary education compared to no education. Immigration background shows a rather surprising result: second generation immigrants are significantly more likely to be found in higher aspiration levels, for first generation immigrants there is no difference to Swiss pupils. Further, there is no effect of different family structures, nor is there a difference between males and females. This stands in stark contrast to the effects found in the previous section for transition probabilities into certifying education.

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 at a low intellectual aspiration level shows no significant effect of hard-to-observe ability (Model 6). The coefficients, however, go into the expected directions. The coefficient of the PISA test score is significantly negative. The inclusion of test scores weakens the effect of observable factors, showing that the significant effect of PISA scores is partially due to the correlation with observable characteristics. It therefore does not fully reflect unpredictable ability. The most important determinants for not being in one of the lowest aspiration levels again are found in the level of compulsory school track and marks in mathematics.
The probit results of models 7 to 8 represent marginal effects for the probability of following a vocational track at *high* aspiration level. According to model 9, hard-to-observe ability is revealed in the sense that *underachievers* are significantly less likely to be found in tracks at a high aspiration level. In turn, *overachievers* are more likely to follow a high-aspiration-level track than their identical peers who perform as expected, whereas the effect is only slightly significant. Observable characteristics play a major role: the track followed at compulsory school level and school marks in mathematics and in the regional language show very large effects. Further, females and second generation immigrants and those with high-educated parents are more likely to be found in the most challenging apprenticeships.

7 Summary and conclusion

In this paper we analyse whether and to what extend 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 (mostly) marked-based upper-secondary education in Switzerland. In the light of the fact that apprenticeship contracts have standardised contents and fixed duration and moreover, leave little scope to adjust wages, employers might try to get far-reaching information on an applicant's ability in the course of the hiring process rather than just relying on easy observable characteristics, that is, statistically discriminating on school marks, level of compulsory school track, gender or family background.

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

Our results suggest that hard-to-observe ability plays a significant role, but in a rather asymmetric manner.

Regarding the probability of directly entering a certifying training, we find that only underachievers are revealed as such, whereas overachievers do not benefit from potentially being better performers than they are able to demonstrate. However, for the sub-group of school leavers that produce evidence of already having successfully passed a sorting process at compulsory school level (tracking), we do not find an effect of hard-to-observe ability, in neither direction.

Hard-to-get information on an applicant's ability also turns out to be important within the sorting process of school leavers into firm-based vocational tracks at different aspiration levels. We find that underachievers are found in less intellectually demanding professions than their outwardly identical peers. In turn, overachievers only have marginally significant better chances to enter an apprenticeship at a higher intellectual aspiration level than otherwise identical school leavers.

Overall, overachievers do not seem to realize profit from actually being better than one would expect, while underachievers face disadvantages in the transition from school-to-work.

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A Descriptive Statistics

Table 1: Variable Definition

Variable	**Definition**
PISA Test Score	Reading literacy test score from the PISA 2000 survey
Underachiever	Equals 1 if observed PISA test score is considerably (1 competence level) lower than predicted by observables, 0 otherwise.
Overachiever	Equals 1 if observed PISA test score is considerably (1 competence level) higher than predicted by observables, 0 otherwise.
Certifying education	Dependent variable: equals 1 if pupil enters a certifying upper-sec. education directly after compulsory school, 0 otherwise (either scholastic and other interim solutions or without education).
Aspiration level	Dependent variable: Aspiration level of 105 vocational tracks (according to expert ratings) from 1 (low) to 6 (high). Variable is 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 rationg is 5 or 6, 0 otherwise.
Female	Equals 1 if female, 0 if male.
Nationality	We distinguish between pupils who are Swiss (born in Switzerland with at least one parent born in Switzerland) and create two dummy variables for immigrants: "Second Generation" equals 1 if pupil is born in Switzerland but parents born outside Switzerland, "First Generation" equals 1 if pupil is also 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 represent 3 categories of highest parental education: compulsory school, upper-sec. education, tertiary education.
Family Structure	Dummies represent 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 or Italian, depending on the linguistic region). Metric scale 1-6 (1=lowest, 4 and higher=sufficent).
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). Metric scale 1-6 (1=lowest, 4 and higher=sufficent).
School: Share of Foreigners	Share of pupils with migration background at school.
Level compulsory school	Dummies for different school tracks that were attended at the time of the PISA 2000 survey. We distinguish between low-level compulsory school (e.g. Realschule), medium-level compulsory school (e.g. Sekundarschule), high-level compulsory school (e.g. Pro-Gymnasium) and "integrated tracks" (no selection, mixed).
Regions (cantons)	Dummies for 22 Swiss cantons (= states).

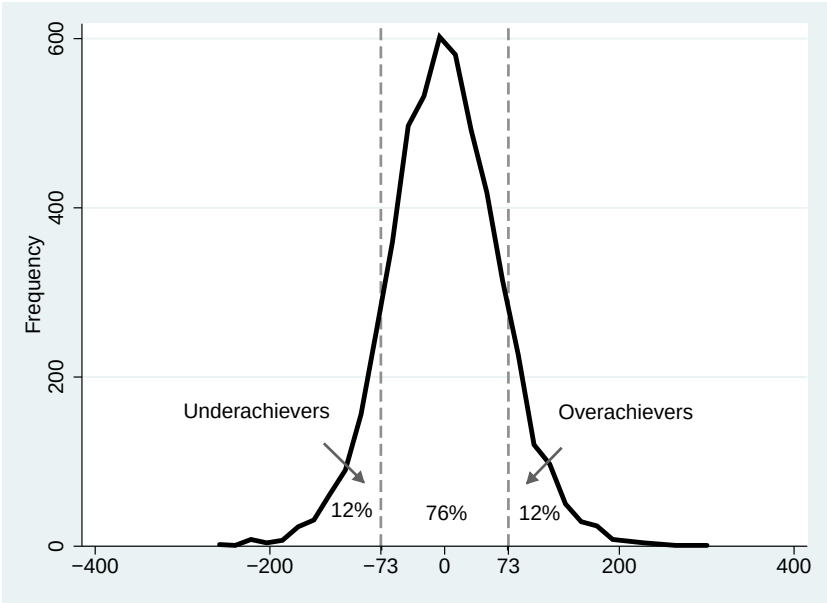
Table 2: Descriptives - univariate and bivariate (with PISA Test Scores)

Continuoues variables (N=2725)	*Mean*	*Std.Dev.*	*Min*	*Max*	*corr PISA*
PISA Literacy Test Score	493.84	80.50	198.04	812.88	1.00
Mark in Test Language	4.87	0.66	1.00	6.00	0.27
Mark in Mathematics	4.80	0.76	1.00	6.00	0.13
Mark in Science	4.97	0.66	1.00	6.00	0.23
School: Share of Foreigners	0.19	0.17	0.00	1.00	−0.21

		Distribution of PISA Test Scores*			
Categorial variables (N=2725)	*Share (%)*	*Mean**	*Std.Dev.**	*Min**	*Max**
Achievs-as-expected	75.5	496.1	63.6	288.2	664.7
Underachiever	12.4	385.1	59.0	198.0	519.2
Overachiever	12.1	591.6	55.5	446.1	812.9
Male	44.3	484.1	80.3	198.0	738.7
Female	55.7	501.6	79.8	250.6	812.9
Swiss	80.5	506.6	74.5	198.0	812.9
Immigrant: second generation	9.6	452.1	81.6	257.7	698.7
Immigrant: first generation	9.9	430.2	83.1	230.1	662.3
Age 15	71.1	502.5	77.9	198.0	812.9
Age 16	28.9	472.5	82.9	255.0	704.3
Parental Education: comp. school	33.1	470.8	82.9	198.0	704.3
Parental Education: sec. II	34.1	506.3	76.9	257.7	812.9
Parental Education: tertiary	32.8	504.2	76.7	257.7	738.7
Family-Structure: nuclear	75.0	497.6	79.5	198.0	775.0
Family-Structure: single	11.5	485.9	81.9	230.1	704.6
Family-Structure: mixed	6.7	482.2	79.5	257.7	812.9
Family-Structure: other	3.8	460.3	87.9	255.0	640.9
Track Lower Sec II: low	35.2	442.5	75.9	198.0	698.7
Track Lower Sec II: medium	61.5	523.2	67.2	230.1	812.9
Track Lower Sec II: no selection	3.3	493.0	81.7	272.0	707.2
Educational status one year after PISA (N=2725)					
Certifying education	70.9	500.8	77.4	198.0	775.0
Non-certifying/no education	29.1	476.9	85.3	230.1	812.9
Aspiration level of dual apprenticeship (N=1167)					
very low (1)	16.5	453.7	75.2	198.0	640.9
low (2)	13.9	464.9	77.4	278.5	676.4
lower medium (3)	13.4	477.6	72.3	268.8	671.7
upper medium (4)	16.8	486.4	71.4	268.1	664.7
high (5)	7.3	528.0	68.9	323.9	668.7
very high (6)	32.2	527.2	64.1	326.4	703.2

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 observed Test Scores from predicted Test Scores estimated by OLS on all observable characteristics (see section 4 and Model 0 of table 3 in the Appendix).
73 Score Points refer to one PISA literacy competence level.

Table 3: Estimation results: Probabilily of directly entering a certifying education

		Probit estimation: 1=direct entry into certifying upper-secondary education, 0 otherwise								
	OLS: PISA Test-Scores	Sample: All			Sample: low-level compulsory track			Sample: medium-level compulsory track		
	(0)	(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				−0.075*			−0.121*			−0.031
				(0.035)			(0.059)			(0.045)
Overachiever				−0.010			−0.035			−0.001
				(0.034)			(0.052)			(0.043)
Female	9.240**	−0.182**	−0.183**	−0.181**	−0.270**	−0.267**	−0.263**	−0.132**	−0.134**	−0.132**
	(3.248)	(0.026)	(0.026)	(0.025)	(0.045)	(0.044)	(0.044)	(0.032)	(0.032)	(0.031)
Immigrant: second generation	−25.309**	−0.060	−0.055	−0.058	−0.131*	−0.127*	−0.129*	−0.008	−0.004	−0.007
	(6.412)	(0.043)	(0.043)	(0.042)	(0.063)	(0.064)	(0.061)	(0.058)	(0.058)	(0.058)
Immigrant: first generation	−38.461**	−0.105**	−0.096*	−0.104*	−0.157**	−0.150*	−0.158**	−0.062	−0.058	−0.063
	(5.717)	(0.041)	(0.041)	(0.041)	(0.059)	(0.061)	(0.061)	(0.058)	(0.058)	(0.058)
Age 16	−15.401**	−0.001	0.002	0.001	−0.026	−0.024	−0.026	0.020	0.022	0.021
	(3.990)	(0.024)	(0.024)	(0.024)	(0.040)	(0.040)	(0.039)	(0.029)	(0.030)	(0.029)
Parental Education: upper sec.	12.395**	0.028	0.026	0.029	−0.013	−0.013	−0.010	0.051+	0.051+	0.051+
	(3.928)	(0.026)	(0.026)	(0.025)	(0.045)	(0.045)	(0.045)	(0.030)	(0.030)	(0.030)
Parental Education: tertiary	9.078*	0.037	0.035	0.037	−0.004	−0.004	−0.005	0.057+	0.057+	0.058+
	(4.176)	(0.026)	(0.026)	(0.026)	(0.046)	(0.046)	(0.045)	(0.030)	(0.030)	(0.030)
Family Structure: single	−4.693	−0.107**	−0.106**	−0.106**	−0.110*	−0.110*	−0.108*	−0.133**	−0.132**	−0.132**
	(4.696)	(0.036)	(0.036)	(0.036)	(0.053)	(0.053)	(0.052)	(0.049)	(0.049)	(0.049)
Family Structure: mixed	−7.443	−0.129**	−0.128**	−0.128**	−0.160*	−0.160*	−0.152*	−0.108+	−0.107+	−0.108+
	(7.439)	(0.044)	(0.044)	(0.044)	(0.069)	(0.068)	(0.067)	(0.058)	(0.059)	(0.059)
Family Structure: other	−15.290	0.044	0.047	0.052	0.066	0.066	0.081	0.067	0.071	0.071
	(9.899)	(0.058)	(0.058)	(0.056)	(0.079)	(0.077)	(0.074)	(0.076)	(0.076)	(0.074)
Mark in Test Language	17.966**	0.025	0.022	0.025	0.010	0.007	0.008	0.027	0.025	0.027
	(2.745)	(0.018)	(0.019)	(0.018)	(0.030)	(0.029)	(0.029)	(0.026)	(0.026)	(0.026)
Mark in Mathematics	6.840**	0.069**	0.068**	0.070**	0.045+	0.043+	0.048*	0.074**	0.074**	0.075**
	(2.422)	(0.015)	(0.015)	(0.015)	(0.025)	(0.025)	(0.024)	(0.020)	(0.020)	(0.020)
Mark in Sciences	13.436**	0.015	0.012	0.014	0.033	0.029	0.032	0.010	0.009	0.010
	(2.734)	(0.019)	(0.019)	(0.019)	(0.030)	(0.031)	(0.030)	(0.025)	(0.025)	(0.025)
School: Share of Foreigners	−15.680	−0.111	−0.109	−0.108	−0.104	−0.101	−0.095	−0.012	−0.011	−0.011
	(12.549)	(0.085)	(0.086)	(0.086)	(0.124)	(0.124)	(0.123)	(0.128)	(0.130)	(0.129)
Track Lower Sec II: medium-level	70.832**	0.140**	0.125**	0.140**						
	(3.868)	(0.022)	(0.025)	(0.021)						
Track Lower Sec II: no selection	24.349**	0.025	0.021	0.017						
	(9.033)	(0.055)	(0.055)	(0.055)						
N	2725	2725	2725	2725	947	947	947	1492	1492	1492
R2, Pseudo-R2	0.395	0.162	0.162	0.164	0.217	0.218	0.224	0.139	0.139	0.140

+ p<0.10, * p<0.05, ** p<0.01, Probit marginal effects at the mean, standard errors computed by delta method (margeff) in parentheses
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 4: Estimation results: intellectual aspiration level of vocational track

	OLS: PISA Test-Scores	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)		
	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PISA Literacy Test Score			0.003**			−0.001**			0.001**	
			(0.001)			(0.000)			(0.000)	
Underachiever				−0.468*			0.071			−0.112*
				(0.190)			(0.048)			(0.045)
Overachiever				0.314+			−0.061			0.080+
				(0.176)			(0.048)			(0.045)
Female	9.240**	0.140	0.100	0.133	0.035	0.045	0.037	0.148**	0.139**	0.147**
	(3.248)	(0.121)	(0.121)	(0.120)	(0.032)	(0.032)	(0.032)	(0.029)	(0.029)	(0.029)
Immigrant: second generation	−25.309**	0.532*	0.607**	0.508*	−0.067	−0.078	−0.063	0.151**	0.170**	0.142**
	(6.412)	(0.228)	(0.225)	(0.222)	(0.051)	(0.049)	(0.050)	(0.056)	(0.054)	(0.055)
Immigrant: first generation	−38.461**	−0.086	−0.001	−0.118	0.002	−0.017	0.006	−0.034	−0.017	−0.048
	(5.717)	(0.225)	(0.222)	(0.219)	(0.051)	(0.049)	(0.051)	(0.058)	(0.058)	(0.057)
Age 16	−15.401**	−0.231+	−0.166	−0.225+	0.046	0.032	0.046	−0.044	−0.025	−0.040
	(3.990)	(0.134)	(0.132)	(0.132)	(0.035)	(0.034)	(0.034)	(0.031)	(0.031)	(0.031)
Parental Education: upper sec.	12.395**	0.471**	0.435**	0.460**	−0.060+	−0.052	−0.059+	0.123**	0.113**	0.119**
	(3.928)	(0.152)	(0.152)	(0.151)	(0.034)	(0.034)	(0.034)	(0.035)	(0.035)	(0.035)
Parental Education: tertiary	9.078*	0.227	0.195	0.199	−0.053	−0.046	−0.048	0.071+	0.063+	0.065+
	(4.176)	(0.153)	(0.152)	(0.150)	(0.037)	(0.038)	(0.037)	(0.037)	(0.036)	(0.036)
Family Structure: single	−4.693	0.142	0.134	0.133	0.012	0.010	0.012	0.033	0.033	0.031
	(4.696)	(0.191)	(0.193)	(0.190)	(0.055)	(0.054)	(0.054)	(0.049)	(0.049)	(0.048)
Family Structure: mixed	−7.443	−0.199	−0.232	−0.254	0.041	0.052	0.052	−0.032	−0.035	−0.038
	(7.439)	(0.257)	(0.263)	(0.255)	(0.064)	(0.064)	(0.064)	(0.054)	(0.053)	(0.052)
Family Structure: other	−15.290	0.137	0.181	0.138	−0.130+	−0.134+	−0.127+	−0.057	−0.041	−0.050
	(9.899)	(0.295)	(0.305)	(0.315)	(0.071)	(0.070)	(0.071)	(0.082)	(0.088)	(0.089)
Mark in Test Language	17.966**	0.251*	0.190	0.248*	−0.012	−0.002	−0.014	0.104**	0.087**	0.102**
	(2.745)	(0.117)	(0.119)	(0.116)	(0.031)	(0.031)	(0.030)	(0.025)	(0.026)	(0.026)
Mark in Mathematics	6.840**	0.307**	0.283**	0.312**	−0.056*	−0.050*	−0.056*	0.069**	0.065**	0.071**
	(2.422)	(0.093)	(0.092)	(0.092)	(0.023)	(0.023)	(0.023)	(0.021)	(0.021)	(0.021)
Mark in Sciences	13.436**	−0.014	−0.043	−0.003	−0.014	−0.007	−0.015	0.003	−0.004	0.007
	(2.734)	(0.096)	(0.096)	(0.096)	(0.026)	(0.026)	(0.026)	(0.024)	(0.024)	(0.024)
School: Share of Foreigners	−15.680	0.907+	0.938+	0.946+	−0.129	−0.137	−0.135	0.248*	0.252*	0.261*
	(12.549)	(0.501)	(0.496)	(0.502)	(0.120)	(0.118)	(0.120)	(0.121)	(0.121)	(0.121)
Track Lower Sec II: medium-level	70.832**	1.940**	1.678**	1.937**	−0.370**	−0.307**	−0.369**	0.456**	0.399**	0.452**
	(3.868)	(0.136)	(0.154)	(0.134)	(0.032)	(0.037)	(0.031)	(0.056)	(0.063)	(0.056)
Track Lower Sec II: no selection	24.349**	0.246	0.225	0.300	−0.085	−0.078	−0.092	0.059	0.054	0.073
	(9.033)	(0.462)	(0.440)	(0.438)	(0.086)	(0.082)	(0.081)	(0.098)	(0.094)	(0.094)
N	2725	1167	1167	1167	1161	1161	1161	1166	1166	1166
R2, Pseudo-R2	0.395	0.323	0.334	0.333	0.177	0.185	0.181	0.285	0.297	0.295

+ p<0.10, * p<0.05, ** p<0.01, Probit marginal effects at the mean, standard errors computed by delta method (margeff) in parentheses
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
Varying sample size due to perfect predictions