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The role of hard-to-obtain information on ability for the school-to-work transition

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Abstract When information about the abilities of job seekers is difficult to obtain, statistical discrimination by employers may be an efficient strategy in the hiring and wage-setting process. In this article, we use a unique, longitudinal survey that follows the PISA 2000 students in their early educational and work–life careers. We find that a deviance in the PISA test scores from what one would have predicted based on easy-to-obtain observable characteristics influences the probability of succeeding in the transition from compulsory schooling to a firm-based apprenticeship significantly but in a non-symmetric way. Only those who had a test result below their predicted result have significantly lower chances of getting an apprenticeship. We also find evidence that the importance of hard-to-obtain information on ability is further revealed in the course of the apprenticeship.

Keywords Statistical discrimination · School-to-work transition · PISA

JEL Classification I2 · J24 · J71

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1 Introduction

Difficulties in identifying the true productive capacity of heterogeneous workers have played an important role in labor 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 missing information.[1]

In this article, we attempt to investigate the effect of easy-to-observe characteristics and hard-to-observe ability on the success of applicants in the transition from compulsory schooling to apprenticeship training. This transition can be seen as a sorting process of young people without labor market experience into firms and into a set of rather standardized jobs, where bad matches are comparatively costly to adjust. Using unique data comprising PISA literacy test scores along with a set of information on individuals that is observable to the hiring firms, we analyze whether and to what extent hard-to-get ability information affects the hiring process and whether there is further revelation of hard-to-observe ability during the subsequent training period.

Firm-based vocational training is the most common post-compulsory certifying education in Switzerland, with more than two-thirds of each cohort opting for this pathway. It 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 leads to a nationally recognized certificate. As an apprentice needs to be hired by a firm for the entire training period, apprenticeship training entails early integration into the labor market (at approximately age 16). Unsuccessful applicants mostly pursue non-certifying intermediate school programs that are designed to increase the prospects on the apprenticeship market the year after.

Employers' screening devices thus play an important role in the sorting process of young adults into vocational education. In the public discussion, stereotyping is claimed to play a (too) dominant role in firms hiring decisions, such that applicants with unfavorable attributes, as low parental socioeconomic status, migration background, low-level compulsory school track attendance and bad school marks, are at a disadvantage to get (good) apprenticeship places, presumably irrespective of their true ability. However, the latter is difficult to assess for firms because, in the absence of uniform school standards and external exams in Switzerland, compulsory schooling outcomes are not well comparable across schools and classes, which in turn reinforces the incentive for firms to take into account additional ability proxies—this may include, for example, family background characteristics— to enhance the accuracy of their ability believes.

Although employment decisions solely based on easy-to-observe factors as described are cheap to make, they may also be costly, especially in the setting of

[1] See 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 2001), wherein information on cognitive ability that is only observable to the researcher, e.g., Armed Forces Qualification Test scores (AFQT), is found to have increasing influence on wages as workers gain experience, indicating that workers' true productivity is gradually revealed over time to the labor market.

apprenticeship training. Economic rationale suggests a potentially high interest among firms in seeking hard-to-get information about ability before selecting apprenticeship applicants: in contrast with ordinary work contracts, apprenticeship contracts cannot be terminated easily[2] and wages for each apprenticeship year as well as training standards are fixed beforehand over the defined training period (3 or 4 years, depending on the training profession). Furthermore, the successful completion of the apprenticeship largely depends on academic performance at the vocational school: A severe mismatch between apprentice and the intellectual aspiration level of the training profession—especially the negative case where apprentices are overwhelmed— potentially results in a drop out of training and, as a consequence, in sunk costs for the training firm.

To test whether a student's hard-to-observe ability is revealed and accounted for within the transition from schooling to market-based upper-secondary education or whether allocation into vocational tracks is solely based on easy-to-observe factors, we make use of the unique longitudinal data set TREE[3] 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. The PISA reading literacy competence test provides us with an ability proxy that is only observable by the researcher, not by recruiters of training firms. We do not claim that this ability measure encompasses all ability dimensions that might be important for firms; however, reading literacy is expected to be an indispensable part of relevant competencies to successfully pass apprenticeship training (especially but not exclusively the school based part of it) and to successfully manage working life afterward. Following the procedure in Farber and Gibbons (1996), we use the test score information in its orthogonalized form, thus already cleaned from the part that is explainable by observables, leaving the ability component that is hard-to-observe for outsiders. We then go one step further and analyze an—as far as we know—unaddressed topic in the existing literature by explicitly differentiating between so-called overachievers and underachievers. This enables us to test whether hard-to-observe ability is revealed and accounted for (if at all) symmetrically. Thereby, we can test separately whether hard-to-observe ability information is gathered and used in favor of those applicants who are—based on the PISA test score— better then they appear to be *(overachievers)* and whether ability is revealed to the disfavor of those students who create an overall outward impression that is better than their (PISA) performance *(underachievers)*.

The remainder of the article is organized as follows: the next section provides an overview of the related literature. In Sect. 3, we present the empirical strategy. Section 4 presents the data and in Sect. 5, we show and discuss the empirical results. Finally, Sect. 6 concludes with a summary and discussion of our findings.

[2] An ordinary working contract can be terminated by the employer without giving reasons, while an apprenticeship contract can be terminated only under certain specified conditions (see http://www.lehr-vertrag.ch/).

[3] As of 2008, Transitions from Education to Employment (TREE) 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).

2 The selection procedure of firms and the role of information on hard-to-observe ability: related literature and hypotheses

Firm-based apprenticeship training requires hiring by an employer willing to train the applicant. The employer and the parents of the apprentice sign a work and training contract that is binding for both parties till the end of the apprenticeship training but does not guarantee further employment once the apprenticeship training is over. The search and selection process for apprenticeship positions 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 or even tests and, finally, receive the apprenticeship post or must continue searching. The latter may be accompanied by a process of adapting expectations about the apprenticeship track aspiration level one might be suited for: after unavailingly applying for high-prestige apprenticeships, applicants might adjust their aspirations downward and begin to apply for less demanding vocational tracks (occupations).

It has been of public concern for several years that finding an (good) apprenticeship post is—irrespective of their true potential—becoming more difficult for compulsory school leavers with unfavorable (easy-to-observe) characteristics.[4]

Recent empirical evidence implies, too, that firms' selection of apprentices is strongly linked to individual background characteristics and former schooling outcomes, whereas the latter are regarded as to provide only limited ability information, too (Haeberlin et al. 2004; Hupka et al. 2006; Imdorf 2006; Neuenschwander and Malti 2009). It is therefore not clear whether the selection practices of firms brings about an allocation that is superior to the one that would be accessible by pure stereotyping on easy-to-observe applicants' characteristics that are correlated with ability.

If the costs to overcome imperfect ability information are sufficiently high, the concept of statistical discrimination predicts that firms base their hiring decisions on all easy-to-observe ability indicators that are assumed to be correlated with the missing information (Phelps 1972; Arrow 1973; Aigner and Cain 1977). Firms are thus assumed to build expectations about an applicants' ability by considering all observable characteristics that provide additional ability information due to different group specific (expected) mean abilities. Whereas this form of stereotyping ("first moment" statistical discrimination) is discriminating on the individual level (there is unequal treatment of actually equal able individuals), it is not discriminating on average and not discriminating against certain groups: there is equal treatment of individuals with equal *expected* ability.[5]

The role of easy-to-observe and initially hard-to-observe ability has been investigated by the employer learning literature by exploiting the US NSLY79 data which contain an ability measure (the Armed Forced Qualification test-scores) that is only

[4] As a consequence thereof, worker's organizations (*Travailsuisse* and the *Association of Commercial Employees*) have published guidelines to sensitize firms for fair selection practices, namely not to place weight on applicant's family background and not to overweight former school types (http://www.zukunftstattherkunft.ch). There has also been launched an online platform that allows preselection of applicants based on anonymized application dossiers that only include information of objective relevance (http://www.weareready.ch).

[5] Unless the case where firms are risk averse and there is unequal variance in productivity across groups.

observable to researchers but hard-to-observe for employers. Farber and Gibbons (1996) find that the part of AFQ test score[6] information that was not predictable by observables at market entry (the residualized test score) becomes increasingly correlated with wages as market experience increases: employers learn. Altonji and Pierret (1997, 2001) simultaneously investigate employer learning and statistical discrimination and find that wages not only become more dependent on a worker's ability (AFQ test-scores) but at the same time also become *less* dependent on easily observable characteristics. These results suggest that firms initially form beliefs about the productivity of a worker using statistical discrimination, i.e., based on educational credentials and ethnicity; as true productivity is revealed over time, firms revise their beliefs accordingly.[7] Using the same data, Lange (2007) finds that employers learn quickly; initial expectation errors decline on average by one-half within the first 3 years and thus restrict the importance for job market signaling of schooling decisions. The tradeoff between screening upon hiring and employer learning has further been found to be different for different educational levels (Arcidiacono et al. 2010); whereas, ability is revealed to the labor market only gradually for high school graduates it is observed nearly perfectly from the very beginning of the careers of college graduates. Information that are typically included in resumes of college graduates and thus are easily observable to recruiters of firms (such as for example college major, grades, or standardized test scores) are, however, not included in the analysis; they are shown to be strongly correlated with AFQ test-scores and thus expected to be a likely explanation for immediate ability revelation in the college market.

In contrast to the described studies our analysis puts its focus more heavily on the time of the hiring process and therefore on the question whether new applicants on the labor market are only evaluated based on their easy-to-observe characteristics (including school marks and level of school track) or whether hard-to-observe ability is detected and used by recruiting firms as well. Due to special institutional circumstances described below we then extend our analysis to test whether hard-to-obtain information on ability affects the labor market entry in symmetric or asymmetric way. The reason for doing so is the hypothesis that firms' expectation error might be subject to an asymmetric risk, too; hiring someone whose ability level considerably lies below the expected level can lead to severe costs as described below, while it is not apparent that firms would profit much in the reverse case.

There are at least three arguments that explain why one expects Swiss training firms to invest considerably in learning about an applicant's ability prior to hiring him or her. Whereas, the first argument is a general one, the second and third arguments demonstrate also the potential rationale for the asymmetry hypothesis.

First, there is a widespread disbelief among firms in the credibility of observable schooling outcomes at compulsory school level (Moser 2004; Imdorf 2009). It arises from the lack of uniform school standards, the lack of standardized tests in compulsory

[6] Farber and Gibbons (1996) only use those parts of the AFQ test that resemble very much the PISA test scores used in this article.

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

schools (grades are only comparable within classes or teachers), the lack of homogeneous curricula and the opaque tracking mechanism into different levels at around age 12.

Second, 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). Training contracts have a fixed duration of 3–4 years—depending on the training occupation—and cannot be terminated as easily as ordinary working contracts. There is no scope for adjusting training content below a defined minimum level (both in terms of topics that must be covered and in terms of complexity that must be taught), nor is it possible to downwardly adjust training wages. Wages are fixed in advance for the entire period of the training contract.

Third, the earlier phase of apprenticeship training is typically related to net costs for firms; some apprenticeship tracks (mostly technical apprenticeships) are associated with considerable firm net investments even until the end of training (Muehlemann et al. 2007; Wolter and Ryan 2011). Premature terminations of apprenticeship contracts are therefore costly, so are efforts and investments of firms to prevent drop outs, e.g., by providing additional coaching in case of arising scholastic problems. Academic difficulties at the vocational school due to a bad match between trainee and the intellectual aspiration level of the vocational track are the primary reason for premature terminations of apprenticeships (Stalder and Schmied 2006) and therefore cognitive skills as measured in PISA should be an important ability information for the training firms.

In line with these considerations it is observed that firms try to diminish the risk of running into problems by investing in learning about a trainee's ability before hiring. They perform screening on the basis of several instruments (see Muehlemann et al. 2007) such as application letters, school reports, interviews, and so-called trial days. Due to the mentioned distrust of firms toward the informational value of school grades and the (intransparent) sorting into school types at compulsory level, some firms are increasingly requiring test results of external screening tests as part of the application dossier. These standardized aptitude tests, sold and administered by specialized private firms and financed by the applicants and their parents, promise to assess the knowledge in school subjects and general cognitive skills to provide information on an applicant's ability to potentially pass the desired apprenticeship training (see Siegenthaler 2011).

However, the observation that a part of the firms try to get superior ability information prior to hiring does not automatically imply; first, that they actually make use of this information in the hiring process; second, that they actually gain ability information that is relevant to predict the desired outcome such as apprenticeship success; and third, that they actually gain ability information that is of additional value compared to easy-to-get information.[8]

[8] Siegenthaler (2011) for example analyzed the informational value for the case of the privately sold aptitude test "multicheck retail sale" and found that the test results do not improve firms' ability to predict apprenticeship success once easy-to-obtain information provided in application dossiers (former school grades and the level of compulsory schooling) is taken into account.

3 Empirical strategy

Successful transition and apprenticeship as explained above are represented by three different dependent variables. A dummy variable indicates whether an applicant succeeds in seamlessly entering certifying firm-based apprenticeship training. A second variable indicates the intellectual standard of the vocational program the successful applicants follow.[9] The third variable reflects the occurrence of problems during training. The exemplary econometric model is thus

$$\text{Successful transition}_i^* = y_i^* = \alpha_i + X_i\beta + B_i^*\pi + \epsilon_i \tag{1}$$

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

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

To test whether hard-to-observe ability influences the success[10] of transition and training, we need an ability measure, B_i^*, that is known to the econometrician and relevant for the transition but, at the same time, cannot be easily observed by recruiters of training firms. If B_i^* is taken into account by employers although hard-to-observe, then its estimated effect $\hat{\pi}$ should significantly differ from zero. If, however, decisions are only made based on easy-to-observe characteristics, the coefficient $\hat{\pi}$ should not be significant.

The variable that allows us to differentiate between observable and unobservable ability is given in our data by the PISA literacy test score. PISA test scores are 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 part of a student's ability, namely, the part that is orthogonal to employers' readily available 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 because it is either included in school reports or is common information in letters of application. As employers might also look out for non-cognitive traits such as motivation, dependability, or social behavior (that reflect other dimensions of ability but are potentially correlated with cognitive ability, too), we include variables

9 The intellectual aspiration level of apprenticeship training is also relevant for the second transition, the one from the apprenticeship training into the labor market. Bertschy et al. (2009) have shown that this level affects the chances of seamless transition in a significant and causal way.

10 Although we define an immediate transition from school to work as a successful transition, this does not mean that all of the unsuccessful applicants would have been better off if they had succeeded immediately in finding an apprenticeship. For some of the unsuccessful candidates the delay of transition might even improve the match between their ability, expectations and the demands of their future employers.

on non-cognitive skills and behavioral information that should be strongly related to information that most employers will observe easily in the course of the hiringprocess.

The unobservable part of ability, 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 almost 40 % of the variance in PISA test scores (see Table 6 in Appendix B), showing that a substantial part of the PISA scores can be determined by characteristics that are easily observable by employers.[11]

We then go one step further and split the residuals, B_i^*, along their sign into two parts: the positive and negative residual PISA score. We also create two dummy variables: The first dummy variable indicates whether a student belongs to the group of *under-achievers*, that is, if actual ability, B_i, lies a considerable amount, t, below the ability level, $E^*(B_i|X_i)$, predicted by observable characteristics (B_i^* is negative and exceeds a certain threshold). The second dummy variable 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 (B_i^* is positive and exceeds a certain threshold). These dummy variables allow us to test whether hard-to-observe ability is revealed symmetrically, if at all, at both ends of the residual distribution.

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

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

We choose the threshold, t, to be a value that has some established implication: t equals 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 as those students whose realized PISA score differs by more than one proficiency level from what would have been expected according to their observable characteristics. Note that the term "-achiever" always refers to the PISA achievement relative to the expectations throughout the article.

To take into account the generated regressor character of predicted PISA test-scores and thus of the dummies for under- and overachievers, we calculated bootstrapped standard errors (1,000 replications).

[11] We have to concede the fact that employers have easy-to-obtain information on the candidates like, e.g., health problems that might be correlated with the PISA results and that are not observable by the researchers. In this case, the additional information available to employers helps them to estimate the true ability more accurately then our own regressions would suggest. This carries the potential risk that the researcher would wrongfully qualify a candidate as an over- or underachiever, whereas the employer had accurately assessed the true ability based on his/her easy-to-obtain information. To minimize the risk of an unjustified classification of the individual, we use a large threshold for the creation of the dummy variables of 73 PISA points (=one proficiency level) around the predicted score. As it is unlikely that an easy-to-obtain information not available to the researchers would influence the predication to such an extend (keeping in mind that we already control for observables that are likely to be highly correlated with information that we might miss), we assume that this potential bias is negligible. As far as this assumption is testable, we do not find evidence for violations ($p = 0.784$ in a RESET test).

4 Data and descriptive statistics

The data set we use is the Swiss longitudinal data set TREE that followed the pupils that had been tested in the Programme for International Student Assessment 2000 (PISA 2000) annually till 2010. The TREE survey is based on the national sample of PISA and thus comprises all respondents who were in the ninth grade and therefore in their last year of compulsory schooling in 2000.[12] This longitudinal data set enables us to observe PISA test scores and individual background characteristics of compulsory school leavers along with detailed information about their further educational and working pathways.

The focus of PISA 2000 was on testing the reading literacy[13] of 15 year olds in 43 participating countries (OECD 2001); mathematical[14] and scientific literacy were investigated only for half of the students. 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 with rather strong social selectivity found for Switzerland.

For the scope of our analysis, we do not exploit the information of the entire TREE sample. We restrict the sample to those compulsory school graduates who were in the apprenticeship market the year after the PISA test, distinguishing between the successful ones, namely, those who take up firm-based apprenticeship training after compulsory school, and the unsuccessful ones who find themselves in some kind of non-certifying interim solution or gap year despite having had applied at least once for an apprenticeship in a firm. This leaves us with 2097 pupils that are observed in PISA 2000 and in the follow-up survey.

As independent variables, other than PISA reading literacy test score results, we use information on those characteristics that are easily observable by employers: The

[12] 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 in which they are enrolled. Because many 15 year olds are already in the 9th grade, the two populations overlap but the national sample of ninth graders is better suited for the purpose of our analyses.

[13] PISA measures competencies in points with a mean of 500 points for all participating countries and a standard deviation of 100 points. PISA reading literacy is measured by a composite test score that summarizes the results from three reading literacy scales. The "retrieving information" scale reports on students' ability to locate information in a text. The "interpreting texts" scale report on the ability to construct meaning and draw inferences from written information. A "reflection and evaluation" scale reports on students' ability to relate text to their knowledge, ideas, and experiences. In addition, experts have divided the scale into six different proficiency levels (very low, low, medium low, medium high, high, very high). For our analysis, we define under- and overachievers to deviate by more than one proficiency level from what one would predict. To give an impression on the difference between two adjacent proficiency levels: students proficient at level 3 (medium low) are capable of reading tasks of moderate complexity, such as locating multiple pieces of information, making links between different parts of a text, and relating it to familiar everyday knowledge. Students proficient at level 4 (medium high) are capable of difficult reading tasks, such as locating embedded information, construing meaning from nuances of language and critically evaluating a text (OECD 2001).

[14] A replication of our estimations for half of the students that have been tested also for mathematical literacy shows qualitatively similar results to the ones presented in this article using reading literacy. Results are available from the authors upon request.

school track at the lower secondary level is represented by a variable with four categories: *high-level school track* that prepares students for high school, *intermediate-level school track*, *basic-level school track* (which has no 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. The PISA data provide us with information on *school marks in the regional (test) language*, *mathematics*, and *sciences*.

The next set of variables we use reflects easy-to-observe information on pupils' individual and parental background as typically specified in the CV of apprenticeship applicants. There is information on *gender*, student's *age* (as some of the ninth graders are 1 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* (born outside Switzerland). Furthermore, 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 also use a set of PISA 2000 variables (OECD 2002) that should be good proxies for information on non-cognitive ability that most employers might observe easily in the hiring process. The index of *instrumental motivation* was derived from students' reports on how often they study to increase their job opportunities, ensure that their future will be financially secure, and enable them to get a good job. A four-point scale was used with response categories almost never, sometimes, often and almost always. The PISA index of *sense of belonging* was derived from students' reports on whether their school is a place where they feel like an outsider, make friends easily, feel like they belong, feel awkward and out of place, other students seem to like them, or feel lonely. The PISA index of *absenteeism* was derived from students' reports on how often they missed school, skipped classes, and were late for school in the two last weeks.[15] We include these measures on non-cognitive ability and social behavior as z-standardized indices into our regressions (mean of zero and standard deviation of 1).

For a complete variable description, see definitions in Table 4 in Appendix A; for descriptive statistics and bivariate relationships with PISA test scores, see Table 5 in Appendix A.

As discussed in Sect. 3, 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 ability information that is not predictable by observable individual or group characteristics. The results of the corresponding OLS regression are presented in Table 6 in Appendix B (model 1c).

[15] Although we have a very rich set of background variables on the students, it is still possible that the employers can collect additional information that is not observable by the researchers. If this information would be correlated with the deviation from the predicted PISA scores, an omitted variable bias would occur. However, to the extent that these unobservables are correlated with the observable characteristics the bias is minimized (see also Footnote 11).

Figure 1 in Appendix B shows the distribution of the residuals resulting from regressing test scores on students attributes. For 79 % of the pupils, the regression model is able to predict PISA test scores within the range of one competence level (73 points). Approximately 11 % of the observations at each end of the residual distribution are identified as *overachievers* (positive deviation larger than one proficiency level) or *underachievers* (negative deviation larger than one proficiency level). For all these observations, realized test scores of under- and overachievers lie outside the 95 % confidence interval of the predicted value.

For the dependent variables, we first analyze by probit regression the indicator of whether somebody who has applied for a training position succeeds in *entering a certifying apprenticeship* directly after compulsory schooling or not. The share of those without an apprenticeship 1 year after the PISA test is 25 %.

The second dependent variable provides information on the *intellectual aspiration level* of the vocational track for those who have started apprenticeship training. The aspiration levels for 101 different vocational tracks were rated on a scale ranging from 1 to 6 by an expert group of vocational advisers (for details and studies using this variable see Stalder 2011).[16]

Approximately 45 % of all apprentices in our sample follow an apprenticeship track of high intellectual aspiration level (5 or 6), e.g., toward a certificate as a commercial employee, IT technician, electronic technician, draftsman, chemist, or optician. Approximately 25 % do an apprenticeship with a low intellectual aspiration level (1 or 2), such as hairdressers, gardeners, bakers, painters, salespeople, florists, cooks, carpenters, or cosmeticians. As shown in Table 5 in Appendix A, there is a relationship in the data between one's reading literacy, as measured by PISA, and the intellectual aspiration level of the vocational track someone follows.[17] Due to the ordinal character of the intellectual aspiration level, we perform ordered probit estimation and present average partial effects for the highest aspiration level.

To test whether hard-to-observe ability has further effects beyond the success of the school-to-work transition, we analyze an indicator that takes a value of 1 for evidence of problems during apprenticeship training, such as repetition of an apprenticeship year, change of training occupation, failure on the final exam, or dropping out of training. The share of apprentices who had at least one of those critical events is 19 % of those who are observable in the data for the standard duration of their training.

5 Results

5.1 Probability of directly entering a certifying apprenticeship training

The first probit model in Table 1 only includes characteristics that are easily observable by firms and might be used by these to form expectations of students' ability. The esti-

[16] We have imputed missing information (1.4 %) about the aspiration level of less common tracks by regressing on training duration (years), amount of vocational schooling lectures (hours per year), and an interaction term between the two. These factors strongly explain the aspiration level (R^2 of 84 %).

[17] PISA test-scores have not been used by the experts to assess the aspiration level.

Table 1 Estimation results: probabilily of directly entering certifying apprenticeship training

Probit estimation: 1 = direct entry into certifying apprenticeship, 0 otherwise

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PISA literacy test score/73		0.014 (0.010)					
Predicted PISA score/73			0.120** (0.015)	0.119** (0.015)	0.118** (0.015)	0.119** (0.015)	
Residual PISA score/73				0.014 (0.011)			
Negative PISA residuals*(−1)/73					−0.041* (0.020)		
Positive PISA residuals/73					−0.014 (0.021)		
Underachiever						−0.063* (0.031)	−0.068* (0.031)
Overachiever						−0.000 (0.031)	−0.003 (0.030)
Female	−0.167** (0.017)	−0.169** (0.017)					−0.168** (0.018)
Immigrant: second generation	−0.107** (0.032)	−0.102** (0.032)					−0.107** (0.032)
Immigrant: first generation	−0.098** (0.029)	−0.090** (0.029)					−0.098** (0.029)
Age 16	−0.017 (0.019)	−0.014 (0.020)					−0.018 (0.019)
Parental education: upper sec.	0.050* (0.021)	0.048* (0.021)					0.049* (0.022)
Parental education: tertiary	0.020 (0.022)	0.019 (0.022)					0.019 (0.023)
Family structure: single	−0.108** (0.025)	−0.108** (0.025)					−0.108** (0.025)
Family structure: mixed	−0.083* (0.032)	−0.083** (0.032)					−0.085* (0.033)
Family structure: other	−0.038 (0.044)	−0.034 (0.044)					−0.033 (0.047)
School mark in test language	0.002 (0.016)	−0.001 (0.017)					0.002 (0.016)

mated average marginal effects show that many of the easy-to-observe characteristics play a statistically significant role. Applicants coming from a medium-level compulsory school track have, e.g., a 9.1 % point higher probability of entering apprenticeship training than those from basic-level tracks. The probability of successfully applying to a firm is, however, highest for those from high-level compulsory schools (with a difference of 19.0 % points). The school mark in mathematics is important as well: having a better mark of one unit [for example a mark of 5.0 (good) instead of 4.0 (sufficient)] increases the probability of successfully applying for an apprenticeship

Table 1 continued

School mark in mathematics	0.048** (0.012)	0.047** (0.012)					0.050** (0.012)
School mark in sciences	0.007 (0.015)	0.005 (0.015)					0.007 (0.014)
Track lower sec II: high-level	0.190** (0.034)	0.168** (0.039)					0.188** (0.035)
Track lower sec II: medium-level	0.091** (0.021)	0.076** (0.024)					0.090** (0.021)
Track lower sec II: no selection	−0.011 (0.070)	−0.014 (0.070)					−0.016 (0.077)
Instrumental motivation	0.007 (0.009)	0.007 (0.009)					0.007 (0.009)
Absenteeism	−0.020* (0.009)	−0.019* (0.009)					−0.019* (0.009)
Sense of belonging	0.012 (0.009)	0.011 (0.009)					0.012 (0.009)
N	2,097	2,097	2,097	2,097	2,097	2,097	2,097
Pseudo R^2	0.164	0.165	0.088	0.089	0.090	0.090	0.166

Average marginal effects, bootstrapped standard errors in parentheses. Reference group: Achieves-as-expected, male, Swiss parents, age < 16, parental education: comp. school, nuclear family structure, low-level compulsory school track, cantons (22) controlled for in all models

$p < 0.10$, * $p < 0.05$, ** $p < 0.01$

by 4.8 % points. In contrast, marks in sciences and in the test language (regional language) seem to have no additional effect.

As for the background variables, females, immigrants (first- and second-generation), pupils with higher absenteeism and those living in single parent households or patchwork families are significantly less likely to be in certifying apprenticeships 1 year after PISA (all else being equal); having parents with upper secondary education (as opposed to compulsory school education) has a positive effect. On the other hand, having parents with tertiary education does not significantly increase the probability of having a smooth transition, although the coefficient goes in the expected direction. Apart from the gender variable, all the coefficients point in the same direction as the coefficients in the PISA test score regression in Table 6 in Appendix B.

Model 2 additionally includes the PISA literacy test score. The test score is scaled (1 = 73 PISA points), so that the effect size can be interpreted as the effect of a variance of 73 PISA points (which is equal to one competence level). The coefficient shows no significant effect on successfully applying for apprenticeship training, implying that hard-to-observe ability would not be relevant for a successful transition. The fact that some of the observable characteristics still have a significant coefficient even when the PISA score is controlled for should not immediately be interpreted as a sign of discrimination of these school leavers as it is highly unlikely, that the PISA score incorporates all relevant information for the employers. Although we cannot exclude discrimination, the coefficients might also indicate that these variables are proxies for other important parts of the prospective apprentices that are taken into account in the hiring process.

Model 3 uses only the part of the hard-to-observe ability that is *predictable* by easy-to-observe characteristics of the applicants. The predicted PISA result thus replaces the easy-to-obtain information. According to the results, an additional predicted competence level would increase the chances to obtain an apprenticeship by 12.0 % points (with $p = 0.000$).

Model 4 additionally includes the part of the PISA test-score that cannot be predicted by observables. This variable is not statistically significant and the point estimate is rather small (equivalent to the 1.4 % points in model 1). Hence, given the difference between the predictable part of the PISA score and the hard-to-obtain part of it, one would deduce that the hard-to- obtain part of the PISA information plays no role in firms' decisions to recruit apprentices.

However, once we differentiate between a positive and a negative residual it becomes obvious that the non-existent effect of the residual is due to the asymmetric impact that the residual has on the probability of a successful transfer into apprenticeship training. If we distinguish between the negative and positive residual in the PISA scores (model 5) and create dummy variables for being either an *underachiever* or an *overachiever* in model 6 (along with predicted PISA) and model 7 (along with all easy-to-observe variables),[18] we see that only a negative deviation from the predicted PISA score seems to matter for employers. School leavers that score at least one competence level below the PISA score that one would have expected based on their easy-to-observe characteristics have a probability for a successful transition that lies almost 7 % points below the probability of school leavers with identical observables. In contrast, school leavers with a substantively higher PISA score than one would have expected have the same probability for a successful transition as less able colleagues with the same observable characteristics.

Contrasting models 5, 6, and 7 additionally shows that using residuals (model 5) or dummy variables for large deviations from the predicted PISA results does not change the results, neither does the inclusion of easy-to-observe variables instead of predicted PISA test scores (difference between models 6 and 7). The result that underachievers have significantly lower probabilities in seamlessly transition from school to apprenticeship therefore is robust across different model specifications.

One might argue that, during the hiring process, employers especially look out for non-cognitive skills or behavioral aspects of pupils, such as motivation, and that if PISA test scores are correlated with these other factors, our estimations might reflect the importance of these non-cognitive factors and not of cognitive abilities, which are already demonstrated through school marks or educational track. We cannot completely rule out such mechanisms, as they are difficult to test. However, including or excluding information that is contained in PISA like *instrumental motivation*, *sense*

[18] We have also estimated models that allow for the possibility that the effect of (positive/negative) residual PISA scores is different in magnitude depending on whether the difference is within the magnitude of one PISA competence level (small) or outside one competence level (the definition for under-/overachievers). Results show that small deviations are neither significantly different from large deviations nor significantly different from zero and thus more spurious.

of belonging, or *absenteeism* (as a behavioral measure at age 15) in all our estimations does not significantly affect our qualitative results.[19]

5.2 Intellectual aspiration level of the dual vocational track

This section describes the empirical results of ordered probit estimations for the question of how hard-to-observe ability components influence the intellectual aspiration level (from 1 to 6) of the apprenticeship track a school leaver successfully enters.

The first model in Table 2 again only includes characteristics that are easily observable for the employer and might be used by outsiders to build expectations of students' ability. The estimated marginal effects show that many easy-to-observe characteristics that are correlated with PISA test-scores (Table 6 in Appendix B) play again a significant role for the sorting into occupations (tracks) with different intellectual aspiration levels. Given the effect sizes, the school track followed in compulsory schooling is the essential criteria for the allocation into the different demanding occupational tracks, besides parental education, school marks, and instrumental motivation.

Including the PISA test-score information in model 2 illustrates that most of the coefficients of those easy-to-observe variables decrease due to the correlation with PISA and that hard-to-observe ability measured by PISA has a highly significant separate effect on the aspiration level: a hard-to-observe difference of one proficiency level leads to a 7.5 % point higher probability of following a highest level vocational pathway.

According to model 4, the unpredictable part of PISA has, however, a much smaller effect than the predictable one, showing that the part of the effect of the observables that also explains differences in PISA scores is the most relevant and only to lesser extent the exact PISA scores.

The subsequent tests for asymmetric effects suggest that the part of ability that cannot be predicted by observables affects the outcome rather symmetrically: the effect of the residuals in both directions amounts to approximately 8 % points (model 5). Likewise, *PISA underachievers* (dummy specification) are on average found in lower aspiration levels, and *PISA overachievers* are found in higher aspiration levels relative to otherwise identical school leavers whose ability is well predicted by easy-to-observe characteristics. Both coefficients of the under- and overachiever dummies are highly significant and approximately 11 % points in magnitude.

5.3 Failure and success in apprenticeship training

Table 3 shows the probit estimation results for having problems during training such as dropping out, repeating a year, changing training occupation or failing the exter-

[19] Estimations excluding non-cognitive variables are available upon request from the authors.

Table 2 Estimation results: intellectual aspiration level of vocational track

Ordered probit estimation: aspiration level scaled from 1 (very low) to 6 (very high)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PISA literacy test score/73		0.075** (0.011)					
Predicted PISA score/73			0.270** (0.015)	0.273** (0.015)	0.273** (0.015)	0.273** (0.015)	
Residual PISA score/73				0.078** (0.010)			
Negative PISA residuals*(−1)/73					−0.075** (0.021)		
Positive PISA residuals/73					0.081** (0.022)		
Underachiever						−0.110** (0.033)	−0.115** (0.032)
Overachiever						0.124** (0.030)	0.113** (0.030)
Female	0.013 (0.020)	0.003 (0.020)					0.010 (0.020)
Immigrant: second generation	0.138** (0.038)	0.156** (0.037)					0.132** (0.038)
Immigrant: first generation	−0.016 (0.036)	0.009 (0.036)					−0.022 (0.036)
Age 16	−0.060** (0.021)	−0.041* (0.020)					−0.063** (0.021)
Parental education: upper sec.	0.078** (0.024)	0.064** (0.023)					0.073** (0.024)
Parental education: tertiary	0.055* (0.024)	0.047* (0.024)					0.050* (0.024)
Family structure: single	0.027 (0.030)	0.029 (0.030)					0.028 (0.031)
Family structure: mixed	−0.014 (0.042)	−0.022 (0.041)					−0.016 (0.044)
Family structure: other	−0.020 (0.044)	−0.009 (0.042)					−0.029 (0.046)
School mark in test language	0.049** (0.017)	0.035* (0.017)					0.048** (0.017)

nal exam. The set of independent variables across models is the same as before, we additionally include the new information on the aspiration level of the vocational track.

The estimation results in Table 3 imply the following: First, hard-to-observe ability has a significant effect: the higher the unpredictable PISA score at the time of application, the less likely are costly events during the apprenticeship period, such as dropping out, repeating a year, changing training occupation, or failing the exam. A higher PISA score of one proficiency level (73 test-score points) decreases the

Table 2 continued

Ordered probit estimation: aspiration level scaled from 1 (very low) to 6 (very high)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
School mark in mathematics	0.058**	0.053**					0.060**
	(0.013)	(0.013)					(0.014)
School mark in sciences	−0.025	−0.034*					−0.023
	(0.015)	(0.015)					(0.015)
Track lower sec II: high-level	0.567**	0.451**					0.569**
	(0.034)	(0.038)					(0.033)
Track lower sec II: medium-level	0.342**	0.270**					0.345**
	(0.023)	(0.025)					(0.022)
Track lower sec II: no selection	−0.081	−0.081					−0.074
	(0.072)	(0.069)					(0.073)
Instrumental motivation	0.041**	0.040**					0.040**
	(0.009)	(0.009)					(0.009)
Absenteeism	−0.001	0.006					−0.000
	(0.010)	(0.010)					(0.010)
Sense of belonging	0.012	0.010					0.013
	(0.009)	(0.009)					(0.009)
N	1,578	1,578	1,578	1,578	1,578	1,578	1,578
Pseudo R^2	0.089	0.098	0.068	0.077	0.077	0.075	0.095

Average marginal effects, bootstrapped standard errors in parentheses. Reference group: Achieves-as-expected, male, Swiss parents, age < 16, parental education: comp. school, nuclear family structure, low-level compulsory school track, cantons (22) controlled for in all models

$p < 0.10$, * $p < 0.05$, ** $p < 0.01$

probability of having problems by approximately 4.5 % points (models 2 and 4). The coefficients for large deviations presented by the under- and overachievers dummies show a rather symmetrical pattern for negative and positive deviations (models 6 and 7).

Second, in comparison with the previous analyses in Sects. 5.1 and 5.2 (initially), hard-to-observe ability has gained in relative importance compared to the ability part that could be predicted by observables.[20] This finding goes in line with labor market theories that postulate that employers learn about ability of their employees as time goes by.

6 Summary and conclusion

The objective of this article is to analyze whether and to what extent employer learning about hard-to-observe ability takes place at the very beginning of a worker's career, namely, in the transition process from compulsory schooling to marked-based upper-secondary education in Switzerland. In light of the fact that apprenticeship contracts

[20] The residual in model 4 has about half of the effect size of the predicted PISA score. In the previous regressions, this relation was 1:8.5 (no significant effect of the overall residual) and 1:3.5.

Table 3 Estimation results: problems in apprenticeship

Probit estimation: problems in apprenticeship: 1 = evidence of problems, 0 = otherwise							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PISA literacy		−0.043**					
test score/73		(0.012)					
Predicted PISA score/73			−0.088**	−0.097**	−0.097**	−0.094**	
			(0.020)	(0.020)	(0.020)	(0.019)	
Residual PISA score/73				−0.045**			
				(0.013)			
Negative PISA					0.051*		
residuals*(−1)/73					(0.024)		
Positive PISA					−0.039		
residuals/73					(0.025)		
Underachiever						0.095*	0.094*
						(0.038)	(0.039)
Overachiever						−0.073*	−0.066^{+}
						(0.035)	(0.034)
Female	−0.022	−0.019					−0.021
	(0.022)	(0.022)					(0.022)
Immigrant:	0.062^{+}	0.048					0.061
second generation	(0.037)	(0.037)					(0.037)
Immigrant:	0.064^{+}	0.051					0.067^{+}
first generation	(0.037)	(0.037)					(0.038)
Age 16	0.050*	0.040^{+}					0.052*
	(0.024)	(0.024)					(0.024)
Parental education:	−0.039	−0.032					−0.036
upper sec.	(0.026)	(0.026)					(0.026)
Parental education:	−0.027	−0.026					−0.026
tertiary	(0.027)	(0.027)					(0.028)
Family structure:	0.059^{+}	0.059^{+}					0.058^{+}
single	(0.032)	(0.032)					(0.033)
Family structure:	0.082*	0.084*					0.082*
mixed	(0.040)	(0.039)					(0.041)
Family structure:	0.054	0.051					0.063
other	(0.058)	(0.057)					(0.061)

have standardized content and fixed duration and leave little scope to adjust prearranged wage profiles over the training period, our first aim was to analyze whether employers try to obtain more revealing information about an applicant's ability *before* hiring rather than only relying on readily available information. We test how deviation in the PISA 2000 test scores from what one would predict based on observable characteristics influences successful transition and training. As the institutional setting may particularly provide incentives for firms to gather and use hard-to-get information to avoid hiring applicants whose ability level considerably lies *below* the expected level (so called *underachievers*), we allow for asymmetric effects of hard-to-get ability

Table 3 continued

Probit estimation: problems in apprenticeship: 1 = evidence of problems, 0 = otherwise							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
School mark in test language	0.014	0.024					0.016
	(0.019)	(0.019)					(0.019)
School mark in mathematics	−0.012	−0.012					−0.015
	(0.015)	(0.015)					(0.015)
School mark in sciences	-0.029^{+}	−0.024					-0.029^{+}
	(0.017)	(0.017)					(0.018)
Track lower sec II: high-level	-0.079^{+}	−0.030					−0.096*
	(0.044)	(0.046)					(0.045)
Track lower sec II: medium-level	−0.034	−0.004					−0.047
	(0.029)	(0.030)					(0.031)
Track lower sec II: no selection	0.068	0.068					0.066
	(0.073)	(0.073)					(0.075)
Instrumental motivation	0.008	0.006					0.006
	(0.010)	(0.010)					(0.010)
Absenteeism	0.016^{+}	0.012					0.014
	(0.009)	(0.010)					(0.010)
Sense of belonging	−0.011	−0.011					−0.013
	(0.010)	(0.010)					(0.010)
Aspiration level (2)	0.056	0.067	0.053	0.063	0.063	0.063	0.068
	(0.043)	(0.043)	(0.045)	(0.045)	(0.045)	(0.044)	(0.045)
Aspiration level (3)	0.092*	0.097*	0.090*	0.094*	0.094*	0.092*	0.096*
	(0.040)	(0.039)	(0.040)	(0.040)	(0.040)	(0.039)	(0.040)
Aspiration level (4)	0.076*	0.090*	0.079^{+}	0.092*	0.092*	0.088*	0.089*
	(0.038)	(0.038)	(0.041)	(0.041)	(0.041)	(0.040)	(0.040)
Aspiration level (5)	0.113*	0.135**	0.114*	0.135**	0.135**	0.124**	0.128**
	(0.044)	(0.044)	(0.046)	(0.046)	(0.046)	(0.044)	(0.044)
Aspiration level (6)	0.095**	0.118**	0.106**	0.128**	0.127**	0.123**	0.117**
	(0.036)	(0.036)	(0.037)	(0.037)	(0.037)	(0.036)	(0.036)
N	1382	1382	1382	1382	1382	1382	1382
Pseudo R^2	0.114	0.122	0.097	0.106	0.097	0.108	0.123

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

information in the hiring process. Second, we analyze whether hard-to-observe ability is further revealed in the course of the apprenticeship period and becomes observable through training outcomes.

Our results suggest that hard-to-observe ability plays a significant role in 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 apprenticeships than their otherwise identical peers. Overachievers, in turn, do not seem to benefit from having more academic potential than one would expect. Therefore, costly-to-observe ability components are only revealed in the hiring process at the lower end of the residual distribution, indicating that firms use pre-market learning in particular to minimize the downward risk of a mismatch.

For the resulting allocation of successful applicants into different intellectually demanding vocational tracks, we find, however, rather symmetric effects; hard-to-get ability information is revealed in a way that significantly increases allocative efficiency at both ends of the distribution.

The results regarding long-term outcomes suggest, however, that there is still additional revelation of ability during the subsequent training period. Apprentices who are PISA overachievers are less likely to face problems, such as dropping out, repeating a year of apprenticeship, changing vocational track or final exam failure. In contrast, PISA underachievers who, despite their lower-than-expected ability, successfully find an apprenticeship are disproportionally more likely to be exposed to these problematic events. The fact that even underachievers who successfully find an apprenticeship show inferior outcomes during the apprenticeship period provides an additional explanation for why firms seem to place more emphasis on detecting under- rather than overachievers in the course of the hiring process.

We show in this article 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 ability are therefore treated differently.

However, due to the nature of our data, we can only observe the outcome of the hiring process and not the behavior of firms themselves. Given the observation that some easy-to-observe characteristics like nationality, school track, or parental background have an impact on these outcomes even after controlling for observable cognitive and non-cognitive competencies, future research should address the question, whether the impact of these characteristics is due to discrimination or whether they stand for information that so far only firms observe but not the researchers.

Finally, our finding that negative and positive hard-to-observe ability surprises are revealed and accounted for in an asymmetric way—presumably depending on labor market or institutional arrangements—could be further tested within the setting of the standard employer learning literature.

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Appendix A: Descriptive statistics

See Tables 4 and 5.

Table 4 Variable definition

Variable[a]	Definition
Certifying education	Dependent variable. Equals 1 if pupil enters a certifying upper-sec. education in the form of apprenticeship training directly after compulsory school; 0 otherwise (non-certifying interim solutions or no education)
Aspiration level	Dependent variable. Aspiration level of 101 vocational tracks (expert ratings) from 1 (low) to 6 (high)
Problems in training	Dependent variable. Equals 1 if apprentice exhibits repetition of apprenticeship year, failure in exam, change in training occupation or drop out
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 aged 16 at the time of PISA 2000; 0 if aged 15
Parental education	Dummies representing 3 categories of highest parental education: compulsory school, upper-secondary 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)
Instrumental motivation	PISA index[b] derived from students' reports on how often they study to increase their job opportunities, to ensure that their future will be financially secure, and to enable them to get a good job (3 items) on a four-point scale with response categories almost never, sometimes, often and almost always
Sense of belonging	PISA index[b] derived from students' reports on whether their school is a place where they feel like an outsider, make friends easily, feel like they belong, feel awkward and out of place, other students seem to like them, or feel lonely (6 items) on a four-point scale with response categories strongly disagree, disagree, agree, and strongly agree
Absenteeism	PISA index[b] derived from students' reports on how often they missed school, skipped classes, and were late for school in the two last weeks (3 items)

[a] All variables except for the outcome variables are measured at the time of PISA 2000

[b] We use the z-standardized indices (mean of 0 and standard deviation of 1) in the regressions

Table 5 Descriptives—univariate and bivariate (with PISA test scores)

	Share (%)	Distribution of PISA test scores*			
		Mean*	Std. dev.*	Min*	Max*
Outcome variables					
Educational status ($N = 2,079$)					
Non-certifying/no education (0)	24.7	480.5	85.2	255.0	812.9
Certifying apprenticeship training (1)	75.3	501.9	75.3	198.0	737.5
Training aspiration level ($N = 1,578$)					
Very low (1)	13.8	457.9	74.5	198.0	640.9
Low (2)	11.0	472.7	78.9	278.5	737.4
Lower medium (3)	12.8	481.9	70.2	268.8	671.7
Upper medium (4)	16.9	493.6	70.6	268.1	670.5
High (5)	9.6	528.7	65.6	327.0	668.7
Very high (6)	35.9	531.6	65.6	300.8	737.5
Problems in training ($N = 1,382$)					
No problems (0)	80.7	511.7	73.7	198.0	737.5
Any problems (1)	19.3	482.4	71.7	298.3	670.5
Independent variables					
PISA literacy test score		496.6	78.4	198.0	812.9
Achieves-as-expected	78.7	497.4	62.5	286.5	643.9
Underachiever	10.3	384.5	57.6	198.0	545.5
Overachiever	11.0	596.0	57.1	446.1	812.9
Male	52.0	492.8	78.4	198.0	737.5
Female	48.0	500.7	78.2	250.6	812.9
Swiss	81.1	508.5	73.6	198.0	812.9
Immigrant: second-generation	8.6	457.5	76.6	283.6	622.5
Immigrant: first-generation	10.3	435.8	77.9	250.6	634.6
$<$Age 16	71.4	504.3	77.0	198.0	812.9
$\geq$Age 16	28.6	477.4	78.7	255.0	704.3
Parental education: comp. school	32.0	474.7	82.2	198.0	738.7
Parental education: upper sec. II	38.3	510.3	73.2	257.7	812.9
Parental education: tertiary	29.7	502.6	75.7	268.1	737.5
Family structure: nuclear	78.2	499.5	78.1	198.0	738.7
Family structure: single	11.7	490.0	75.8	267.1	697.3
Family structure: mixed	6.5	493.9	73.9	257.7	812.9
Family structure: other	3.5	457.9	91.3	255.0	670.5
Track lower sec II: no selection	5.7	491.8	71.8	272.0	676.1
Track lower sec II: low	33.1	444.4	73.7	198.0	653.8

Table 5 continued

	Share (%)	Distribution of PISA test scores*			
		Mean*	Std. dev.*	Min*	Max*
Track lower sec II: medium	44.7	521.7	67.0	294.9	812.9
Track lower sec II: high	16.5	535.0	61.4	357.3	738.7
	Mean	Std. dev.	Min	Max	Corr PISA
Mark in test language	4.74	0.61	1.00	6.00	0.22
Mark in mathematics	4.71	0.77	1.00	6.00	0.10
Mark in science	4.86	0.66	2.00	6.00	0.20
Instrumental motivation	2.87	0.73	1.00	4.00	0.02
Absenteeism	1.30	0.45	1.00	4.00	−0.16
Sense of belonging	3.31	0.52	1.00	4.00	0.08

Appendix B: Figures and tables

See Table 6 and Fig. 1.

Table 6 Estimation results: OLS PISA literatcy test scores

	(1)	(2)	(3)	(4)
Female	6.607*		6.478*	6.921*
	(3.184)		(2.829)	(2.826)
Immigrant: second generation	−37.021**		−25.557**	−23.665**
	(6.057)		(5.085)	(5.063)
Immigrant: first generation	−56.198**		−33.927**	−33.093**
	(5.708)		(4.837)	(4.791)
Age 16	−23.756**		−18.439**	−17.655**
	(3.628)		(3.200)	(3.199)
Parental education: upper sec.	19.101**		10.677**	11.126**
	(4.077)		(3.478)	(3.476)
Parental education: tertiary	15.227**		5.477	6.111^{+}
	(4.239)		(3.597)	(3.576)
Family structure: single	−7.592		−1.812	−0.966
	(4.803)		(4.199)	(4.167)
Family structure: mixed	−5.159		3.127	3.650
	(6.429)		(5.776)	(5.770)
Family structure: other	−37.120**		−20.128*	−18.052*
	(9.540)		(9.205)	(8.995)
School mark in test language		17.840**	14.764**	14.881**
		(2.674)	(2.670)	(2.675)
School mark in mathematics		4.705*	4.769*	4.431*
		(2.022)	(1.995)	(1.997)
School mark in sciences		12.429**	10.143**	9.885**
		(2.575)	(2.502)	(2.512)
Track lower sec II: high-level		124.446**	113.028**	112.258**
		(5.723)	(5.663)	(5.647)

Table 6 continued

	(1)	(2)	(3)	(4)
Track lower sec II: medium-level		82.060**	73.878**	73.441**
		(3.761)	(3.651)	(3.624)
Track lower sec II: no selection		7.267	4.763	7.972
		(10.149)	(9.554)	(9.532)
Instrumental motivation				−0.224
				(1.418)
Absenteeism				−6.237**
				(1.548)
Sense of belonging				2.594+
				(1.413)
Constant	495.542**	269.332**	302.840**	304.532**
	(6.682)	(17.332)	(17.382)	(17.587)
N	2,097	2,097	2,097	2,097
R^2	0.180	0.340	0.388	0.395

Robust standard errors in parentheses. Reference group: male, Swiss parents, age < 16, highest parental education: compulsory school, nuclear family structure, low-level compulsory school, cantons (22) controlled for in all models

$^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$

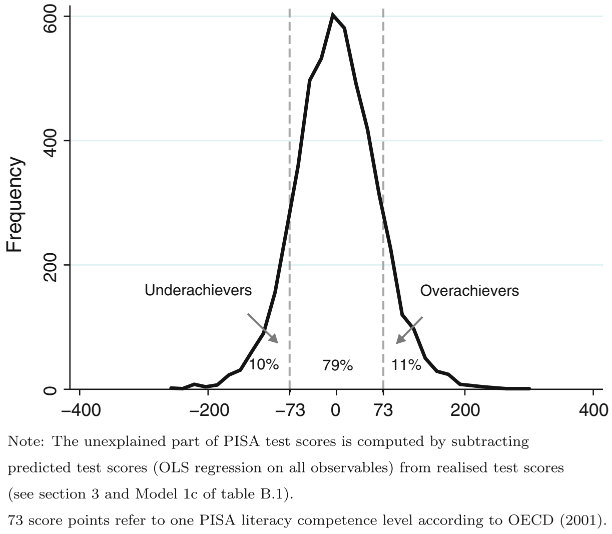

Fig. 1 Distribution of unexplained PISA test scores (residuals). *Note* The unexplained part of PISA test scores is computed by subtracting predicted test scores (OLS regression on all observables) from realised test scores (see Sect. 3 and model 1c of Table 6). 73 score points refer to one PISA literacy competence level according to OECD (2001)

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