Performance of young adults:

The importance of cognitive and non-cognitive skills

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Abstract

Using Norwegian register data, we estimate the impact of cognitive skills (grades in Mathematics and Science) and non-cognitive skills (grades in behavioral and practical subjects) measured at age 16 on high school graduation and labor market attachment for young adults. We find strong effects of both kinds of skills on all outcomes. Cognitive and non-cognitive skills are equally important for high school graduation, while non-cognitive skills are most important for the probability to receive welfare benefits or being inactive at age 22. Finally, we perform an analysis of the causal effect of cognitive training exploiting that some students are randomly selected at age 16 to sit for an external high-stake exit examination in Mathematics. The selected students are exposed to a few days of intensive training. This intervention is found to have a positive effect on the probability of high school graduation for males.

May 2012, **preliminary draft**

Keywords: Cognitive skills; Non-cognitive skills; Cognitive training; High school graduation

JEL Classification: I21; J24

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1. Introduction

A number of studies have found that student cognitive ability as measured by test scores in mathematics and science are important predictors of future earnings and other individual outcomes, see Hanushek (2002) for a review of the evidence. Moreover, recent cross-country studies suggest that aggregate measures of test scores are important determinants of economic growth and development (Hanushek and Woessmann, 2008).

However, it is still not clear to what extent the impact of test scores and other achievement measures reflect pure cognitive skills or if they indirectly also capture the effect of other personality traits such as motivation and conscientiousness. This has initiated a growing literature that emphasizes in more detail the skill formation process and in particular the role of non-cognitive skills, see Cunha and Heckman (2007). The evidence indicates that non-cognitive skills explain as much of the variation in earnings and employment prospects as cognitive skills.

However, while cognitive skills are measured by some test scores, measures of non-cognitive skills are usually based on survey data.[1] Weaknesses with self-reported information, combined with inherent difficulties in distinguishing conceptually between cognitive and non-cognitive skills, suggests that further empirical studies using new types of data can enhance our understanding of the role of different types of skills.

The present paper includes two contributions. First, we use detailed information from transcript of records at the end of compulsory education at age 16 in Norway instead of survey information on non-cognitive skills. The individual records contain 13 grades in different subjects. Thus, we estimate the effect of the skills that are regarded as important by the school system and evaluated objectively by teachers. Following the literature, we measure cognitive skills by average grade in Mathematics and Science. Non-cognitive skills are measured by grades in “behavioral and practical” subjects such as Arts and crafts and Physical education. Our argument is that achievement in such subjects, conditional on cognitive skills, mainly reflects characteristics such as

[1] Heckman et al. (2006) and Carneiro et al. (2007) measures non-cognitive skills by self-reported loss of control and self-esteem, while other papers rely on the popular five-factor model shaping human personality developed concept in the psychology literature (Digman, 1990, Mueller and Plug, 2006, Borghans et al. 2008).

conscientiousness and openness to experience, which are elements in the popular five-factor model of personality structure. For example, teacher assessed grades in Physical education reflects engagement, preferences for following rules and motivation rather than particular performance in sports.

We relate the skill measures to high school graduation, labor market attachment and the probability to receive welfare benefits for young adults using data for the cohorts leaving compulsory education in 2002–2004. We find strong effects of both kind of skills, and that the estimate of cognitive skills is biased by exclusion of non-cognitive skills from the empirical model.

Even though the models condition on a rich set of individual characteristics and fixed school effects, the fact that the skills have strong predictive powers do not necessarily imply a causal effect in the sense that an intervention which successfully increases skills would have the same impact. Our second contribution is a causal study exploring a random intervention in cognitive training. At the end of Norwegian compulsory education, about 40 percent of the students are randomly selected to sit for an external exit examination in Mathematics while the rest of the students have an examination in Norwegian or English language. The students are informed of their exam subject about a few days in advance, such that there is a period of intensive training with extensive support from teachers. Even though the intervention period is relatively short, the strong effect of cognitive skills estimated in the first part of the paper combined with a large sample imply that identification of significant effects should be possible.

The analysis of the intervention in cognitive training is related to a small, but growing literature investigating the impact of high school curriculum initiated by Altonji (1995). The typical finding is that more mathematics courses in high school increases educational attainment and earnings. The identification issue in this literature is not trivial, however, since instruments for the choice of coursework are not easily available. The experimental setting that we exploit provides evidence of whether the often observed relationships between cognitive skills and educational and labor market outcomes represent causal effects or merely student sorting.

The paper is organized as follows: Section 2 reviews related literature while Section 3 presents relevant institutional settings in Norway and the data. The empirical specification and the empirical results for the model including cognitive and non-cognitive skills measured by grades are in Section 4, while Section 5 includes the causal analysis of cognitive training. Section 6 contains concluding remarks.

2. Related literature

Cognitive skills are associated with intelligence and the ability of problem solving. A number of papers have investigated the impact of such skills measured by test scores in mathematics and science on earnings and to some extent also on other individual outcomes. To take a few representative studies; Bishop (1989), Murnane et al (1995), and Altonji and Pierret (2001) all find that measures of achievement is important determinants of individual earnings for given educational attainment and observed individual and family characteristics. Koedel and Tyhurst (2012) use a resume-based field experiment and find that stronger mathematic skills improve labor market outcomes.

Motivated by the micro-econometric evidence, some recent studies assess the role of cognitive skills for economic growth and development. Hanushek and Kimko (2000) and Hanushek and Woessmann (2008, 2009) all find that cognitive skills as measured by aggregate scores on international comparable student tests in Mathematics and Science have a sizeable positive effect on economic growth.

A related literature has studied the impact of school curriculum on individual earnings, following the seminal paper by Altonji (1995). These studies typically ask to what extent earnings depend on the number and levels of math and science courses taken in high school. A difficult question is whether the estimated impacts of skills in different subjects can be interpreted causally or if they represent selection effects or omitted variables. For example, individuals with unobserved characteristics generating higher earnings may have chosen more advanced mathematics courses. However, given the problem to find credible instruments for students' coursework, or other credible identification strategies, see Altonji et al. (2012), it is not surprising that the results vary somewhat across studies.

For the US, Altonji (1995), Levine and Zimmerman (1995) and Rose and Betts (2004) generally find significant positive impacts of taking more math and science courses on earnings, although the strength of the relationship varies between studies. Two recent studies have used curriculum reforms and pilot schemes to identify the impact of curriculum on earnings. Goodman (2009) uses US state-level changes in high school math requirements as instruments for students' actual coursework and find that additional math coursework increases earnings, especially for low-skilled students. Joensen and Nielsen (2009) explore a pilot scheme implemented in some Danish high schools where students were allowed to select different combinations of high school courses than students enrolled in other schools. Using this variation as instrument for students actual choices, their results show that taking more advanced Math courses during high school have a significant and sizable positive impact on earnings. Interpreted causally, their estimates imply that taking more math increases earnings by 20-25 percent and the main part of this effect is through the increased likelihood of taking higher education.

The literature on the role of cognitive skills has been challenged by authors arguing that some of the estimated effect of cognitive skills in reality captures the impact of non-cognitive skills. Non-cognitive skills are much more difficult to define and measure than cognitive skills. A popular taxonomy of non-cognitive skills is given by the five-factor model shaping human personality: agreeableness, conscientiousness, emotional stability, extraversion and autonomy. Extensive discussion of these concepts is given in Digman (1990), Mueller and Plug (2006) and Borghans et al. (2008).

Psychologists and sociologists have a long tradition in studying the role of non-cognitive skills in shaping individual behavior and outcomes using survey data. Jencks (1979) found that personal traits as leadership, industriousness, and perseverance had substantial impact on individual earnings and educational attainment holding family characteristics and cognitive skills constant. Recently, a number of papers by Heckman and coauthors have brought the role of non-cognitive skills to the forefront in the economics of education and skill formation literature. An instructive example of the potential role played by non-cognitive skills is provided by Heckman and Rubin (2001). They show that recipients of degrees from the general education development program (GED) had lower wages, and less schooling than ordinary high school graduates, and comparable or even less than high school drop-outs holding cognitive skills constant. Heckman et al (2006) use US national Longitudinal Survey of Youth (NLSY) data to estimate the impact of different skills on earnings, schooling and occupational choice within a structural latent factor model. They find that non-cognitive skills measured by self-reported indicators of loss of control and self-esteem strongly influence schooling decisions wages. Carneiro et al (2007) find similar results for UK.

The studies above use self-reported survey data on non-cognitive skills. In addition to possible measurement error, self-reported measures may themselves be interpreted as outcomes. Two recent papers address this concern by using data on non-cognitive skills based on external evaluations. Lindquist and Vestman (2011) investigate the association between male wages and labor market attachment and cognitive and non-cognitive skills using data from the Swedish military enlistment. A novel feature of their study is that they measure non-cognitive skills based on an external evaluation conducted by psychologists using interviews with each individual while cognitive skills are based on IQ tests. They find that while cognitive skills is generally the most important determinant of male wages, non-cognitive skills turns out to be more important for low skilled workers and earnings below the median. Further, non-cognitive skills are more important than cognitive skills for the probability to receive unemployment support and social assistance.

Segal (2011) uses NELS data from the US and studies the impact of premarket teacher reported student misbehavior in eigth grade (tardiness, absence, disruptiveness etc.) on male labor market outcomes and education attainment (probability of obtaining a post-secondary degree). She finds that, controlling for test scores in mathematics and reading, educational attainment for males is negatively correlated with misbehavior. Her results are broadly consistent with the findings in Lindquist and Vestman (2011) on the relationship between earnings and different types of skills in Sweden.

Lindquist and Vestman (2011) and Segal (2011) only consider the impact of cognitive and non-cognitive skills on outcomes for males. Our approach using register data on student grades in mathematics and science as a measure of cognitive skills and grades in practical subjects such as arts and crafts and physical education as a measure of non-cognitive skills allows us to infer the impact of different skills using the total student population. In particular, it allows us to investigate whether the reward to different skills differs by gender.

In addition to the general literature on the impact of cognitive and non-cognitive skills, some authors have studied the relationship between individual outcomes and participation in physical activity and sports, see Barron et al (2000), Pfeifer and Cornelissen (2010) and Rees and Sabia (2010). Most of the studies find that participation in such activities increase school performance, years of schooling and future earnings even when controlling for cognitive skills. These results may reflect that non-cognitive skills are important factors explaining participation in physical activity and sports or that participation increase non-cognitive skills. A recent study by Rooth (2011) uses data from fictitious applications to real job openings in Sweden and finds that applicants signaling sports skills had a significantly higher callback rate. Moreover, based on military enlistment data similar to that used in Lindquist and Vestman (2011) he find that physical fitness as measured by a test score on physical work capacity and body weight has a significant impact on male earnings. For our work it is interesting to note that most of the physical fitness premium seems to be attributable to non-cognitive skills.

3. Institutions and data.

3.1. Institutions

The Norwegian school system consists of ten compulsory years, where the first seven years are attained in primary schools and the last three years in lower secondary schools. Students are normally enrolled the year they turn six years old. There is no possibility to fail a class, which implies that everybody finish compulsory education 10 years after enrollment. However, the weakest students do not get a grade in every subject.

At graduation the students receive a diploma containing 13 different grades set by teachers and exam results. Table 1 gives an overview of the subjects. The grading system consists of a scale from one to six, where six is the highest grade. Teacher grades are based on the achievement throughout the 10th school year. Casual evidence provided in Prøitz and Borgen (2010) clearly indicates that effort and behavior matter in addition to skills in the "behavioral and practical" subjects.

All students have to sit for a written external exit examination at the end of compulsory education in either Norwegian language, English language or Mathematics.[2] The Norwegian Directorate for Education and Training prepares the exams, while local authorities are responsible for the assignment of examination

[2] In addition, about two thirds have an oral examination in one of the subjects on the curriculum. The oral examination is organized by the school district in cooperation with the individual schools, without any influence by the Directorate for Education and Training. Our data indicates that the allocation of students across subjects is not random. In particular, students without an oral examination tend to have low teacher grades.

subjects to schools and individual students. Clear instructions about randomization are given by the Directorate. The length of the period from the students are informed about their exam subjects to the examination day varies across the years, but ranges from two to five working-days in the empirical period of the paper. During this period the students are expected to work only with preparation for the exam, and their teachers provide extensive support. We give a closer description of the exam system in Section 5, in which we exploit the randomization to estimate the causal effect of training in Mathematics..

After the end of compulsory education, students can choose to leave school or to enroll in high school education. In high school students, can choose between 15 different study tracks. Three of the study tracks qualify for higher education (academic tracks) and 12 tracks give a certificate for work in a broad amount of occupations (vocational tracks). The academic tracks consist of three years, while the vocational study tracks normally consist of two years in school plus two years as apprentice.

About 95 percent enroll high school the year they finish compulsory education. Students have to rank three different study tracks when applying for enrollment. All students have a legal right to be enrolled in one of these three tracks, but at which track and school they get a study place depends on achievement in compulsory education measured by their teacher grades and the results on the exit examination.

Public schools have a common curriculum and the same number of teaching hours in each subject[3]. The 430 municipalities are responsible for compulsory education, while the 19 counties are responsible for high school education. The municipalities use about one-fifth of their budget on education, while the counties spend over 50 percent on education. Enrollment into compulsory schools is based on catchment areas, while the counties have major leeway on enrollment in high schools. They determine the capacity of the individual schools and study tracks according to local needs and student demand. Some counties use catchment areas for the individual study tracks, other counties have free school choice within certain regions, while some do not have any restrictions on school choice.

[3] Few students enroll in private schools. About two and five percent of a cohort enroll in private compulsory schools and high schools, respectively.

3.2. Data

We use register data from Statistics Norway covering all students that finished compulsory education in the years 2002-2004. The 2002-cohort is the first cohort with grade information in the registers. To make the sample more homogeneous we only include students that turn 16 years of age the year they finish compulsory education in the empirical analysis.[4] In addition, we only include students with grade information on all relevant subjects and information on which compulsory school they graduated from. The data reduction is presented in Table 2. The analytical sample consists of 88.8 percent of the population, amounting to 154,515 observations.

We apply the teacher assessed grades to calculate measures of cognitive and non-cognitive skills. Following the literature, cognitive skills are defined as the average grade in Science and Mathematics. For non-cognitive skills we utilize that in "practical and behavioral" subjects, traits as conscientiousness, openness to experience, engagement and motivation are valued. Thus, we use the average of the grades in the subjects Food and health, Arts and crafts, Physical education, and Music. Recognizing that cognitive skills might improve the grades also in these subjects, interpreting results as effects of non-cognitive skills require that the model condition on cognitive skills. Similarly, non-cognitive skills might improve grades in cognitive subjects. Thus, analysis that does not include measures of non-cognitive skills might overestimate the importance of cognitive skills.[5]

Appendix Table A1 presents the distribution of the grades set by teachers in each subject, while mean values and standard deviations are presented in Table 1. The average grade is lowest in Mathematics and highest in Physical education. While 23 percent of the students obtain grade 1 or 2 in Mathematics, that is the case for less than 6 percent in Physical education, Food and health, Arts and craft, and Music.

[4] Since no students fail any grade in Norwegian compulsory education, one could expect that all students turn 16 years of age the year they finish compulsory education. However, there are some exceptions. If a child is not considered to be mature enough, the parents together with the school and psychologists can postpone enrollment one year. It is also possible to start one year ahead the birth cohort. In addition, some older students return to improve their grades and immigrants are often over-aged.

[5] The correlation coefficient between the measures of cognitive and non-cognitive skills is 0.74, which clearly indicates that there are some common characteristics important for performance in both cognitive subjects and "practical and behavioral" subjects.

The standard deviation of the mean grade in Mathematics and Science is larger than the standard deviation of mean grade in the non-cognitive subjects. To make estimates comparable, we use standardized values with mean zero and standard deviation equal to unity in the empirical analyses. The distributions of the standardized variables are presented in Figure 1. While the distribution of cognitive skills is close to the normal distribution, some individuals have non-cognitive skills more than three standard deviations below the mean.

Table 3 gives a description of high school graduation. About 57 percent graduate within expected time, while additionally about 14 percent graduate delayed but within 5 years after the end of compulsory education. These numbers imply that a large fraction of the students drop out of high school education during the high school years. Table 3 shows that there are small differences across the cohorts. Figure 2 present the separate distributions of cognitive and non-cognitive skills for graduates and dropouts. Panel A shows that the distribution of cognitive skills for individuals that graduate high school within five years is clearly to the right of the distribution for dropouts. Panel B shows a similar picture for non-cognitive skills.[6]

The analysis of the impact of cognitive and non-cognitive skills on labor market attachment is restricted to the 2002-cohort since the relevant data have not been available after 2008. The 2002-cohort turns 22 years of age in 2008. Since higher education is common at this age, we focus on the probability of receiving welfare benefits and the probability of inactivity, where the latter is defined as not registered in employment or in any education.

Welfare beneficiaries are registered with the number of months receiving benefits during the calendar year. We use the share of the months with benefits in the analysis. Table 4 shows that on average 1.7 percent of the 2002-cohort received benefits in a random month in 2008. This share is markedly lower for individuals graduating high schools within five years, i.e., no later than spring 2007 (0.3 percent) than for dropouts (4.9 percent). During 2008 4.5 percent of the 2002-cohort received welfare benefits at least one month.

[6] The skill variables are discrete, but the presentations of the distributions in Figure 2 are smoothed by the choice of bandwidth. Mean value of standardized cognitive skills is 0.32 and -0.79 for graduates and dropouts, respectively. The corresponding numbers for non-cognitive skills are 0.31 and -0.76.

Since employment is registered on a daily basis, we measure inactivity on a specific day. We present results for the status October 15th 2008. Table 4 shows that 15.9 percent is inactive this day, with large differences between high school graduates and dropouts. About the same share of those not inactive are registered in education and in employment. Separate distributions of cognitive and non-cognitive skills for both inactive and active individuals are shown in Figure 3. Both panel A and B show the same pattern as in figure 2, where the distribution of cognitive and non-cognitive skills for not inactive individuals is clearly to the right of the distribution for inactive individuals.

Individual characteristics and family background are well documented as factors affecting individual outcomes. In the empirical analysis we include variables for gender, immigration, birth quartile, domestic mobility, whether the student need support related to diseases and disabilities, parental education, parental income, parental employment status, and parental marital status. Domestic mobility is defined as living in different municipalities at age 7, 13 or 16. Parental education is classified into four levels (only compulsory education; graduated from high school; bachelor degree; master or PhD degree), and our measure is based on the education for the parent with most education. Parental income is represented by the level of taxable income and its square. For marital status, two dummy variables are included in the model; one if parents are married when the student graduate from compulsory education and one if the parents are divorced at that time. 61.5 percent of the parents were registered as married, 12.5 percent were registered as divorced and 26 percent had never been married. Descriptive statistics are presented in Appendix Table 1.

4. Cognitive and non-cognitive skills

We start the analysis by estimating the impact of cognitive and non-cognitive skills as measured by average grades at age 16. Since the cohorts in the analysis are relatively young, we focus on high school graduation, but we present also results for the probability to be neither employed nor in education and the probability of welfare participation at age 22.

To estimate the impact of cognitive and non-cognitive skills, we use a simple regression model as shown in equation (1). When the outcome is high school graduation, the dependent variable, Y_{ijc}, is a binary variable that equals one if student *i* from compulsory school *j* in cohort *c* has graduated high school education. Cognitive skills (*cog*) are defined as the mean grade in Mathematics and Science, and non-cognitive skills (*noncog*) are defined as the mean grade in Physical education, Food and health, Arts and craft, and Music. If $\beta_1 > \beta_2 \geq 0$, cognitive skills are more important than non-cognitive skills, and vice versa. X_{ic} is a vector of individual characteristics. In addition, the model includes interaction between cohort (θ_C) and the compulsory school from which the student graduated (γ_j). These fixed effects control for all systematic differences in grading practices between schools and cohorts as well as other school and cohort characteristics that potentially affect high school graduation. Below, we also present results for alternative sets of fixed effects, including detailed neighborhood fixed effects. ε_{ic} is a random error term.

$$(1) \quad Y_{ijc} = \alpha + \beta_1 cog_{ic} + \beta_2 noncog_{ic} + X_{ic}'\delta + \gamma_j * \theta_c + \varepsilon_{ic}$$

As robustness checks, we provide estimates using more flexible model formulations. We estimate none-parametric specifications, and models with the grades in every subject included rather than averages over several subjects.

We begin with an analysis of the probability to graduate from high school, with the main emphasis on graduation within five years after the end of compulsory education, consistent with the legal rights for the students. We also make a distinction between graduation on-time and delayed. The last part of the section presents results for additional outcomes at age 22.

4.1. High school graduation

Table 5 presents the estimated effects of cognitive and non-cognitive skills on the probability to graduate from high school within five years after the end of compulsory education (the year the individuals turn 21). The first column presents the correlation between skills and graduation. Increasing cognitive skills with one standard deviation is associated with 14.3 percentage points (20 percent, evaluated at sample mean) higher graduation probability, while a similar change in non-cognitive skills is associated with 11.7 percentage points (17 percent) higher graduation probability. These are large effects.

Column (2) in Table 5 includes socioeconomic characteristics. Even though several of the socioeconomic characteristics are strongly related to the probability to graduate (see below), the effects of cognitive and non-cognitive skills are only marginally reduced when they are included. However, cognitive and non-cognitive skills are correlated. Column (3) shows that the effect of cognitive skills increases to 19.4 percentage points when non-cognitive skills is excluded from the model, an increase of 47 percent. This result clearly indicates that estimates of cognitive skills are biased in models not taking other kinds of skills into account.[7]

One concern is that grading standards can vary across schools, introducing biased estimates. In this case we would expect the coefficients in column (2) in Table 5 to be underestimated. This concern is probably of less importance for our measure of cognitive skills since external exit exams in Mathematics provide a check on grading practices. Systematic differences in grading standards might be a more important concern for our measure of non-cognitive skills. Since we expect grading practices to vary more across schools than across classrooms within schools, school fixed effects will reduce the potential bias. The model in column (4) includes school fixed effects, which increases the effect of non-cognitive skills, but does not change the effect of cognitive skills. If grading practices varies greatly across classrooms within schools, we would expect cohort specific school fixed effects to further increase the estimated effects since a teacher usually teaches the same group of students in several years. However, the results for the model including cohort specific fixed school effects (column (5) in Table 5), that is the model in Equation (1) above, are basically identical to the previous model. Finally, in order to control for neighborhood effects, the model in column (6) in Table 5 includes cohort specific ward fixed effects. This model formulation accounts for detailed neighborhood characteristics since, in each cohort, the average number of students in the ward is only 4.8. However, also in this highly flexible model specification, the effects of our measures of cognitive and non-cognitive skills are similar to those obtained in the simpler models.

The full results for the model in column (5) in Table 5 are reported in Appendix Table A2, column (1). The estimated effects of the socioeconomic characteristics are mainly as expected. Conditional on cognitive and non-cognitive skills, individuals with married and working parents who have more than compulsory education have a higher

[7]. In models with school times cohort fixed effects (column 5 in Table 5), the bias is even larger (62 percent).

probability to graduate. The effect of income is positive except for the students with the very highest parental income. Females and individuals born late in the year also have a higher graduation probability, where the latter effect must be interpreted as a catch-up effect since those born late have lower measured skills (Bedard, 2006).[8] In addition, mobility during compulsory education and disability status is negatively related to graduation, while immigrants have a higher graduation probability than native Norwegians. The latter effect is critically dependent on parental characteristics included in the model.

The effects of skills may be non-linear. Figure 4 presents results from a model with non-parametric effects of cognitive and non-cognitive skills using the model formulation with cohort specific school fixed effects (column (5) in Table 5). The figure presents estimated skill effects relative to students with normalized skills equal to zero (mean skills). For both cognitive and non-cognitive skills, the effects are small in both tails of the skill distribution, and close to linear for skill levels with the highest density; in the range -2 to 1 in the standardized distribution of skills.[9]

By classifying skills into only two categories, we do not utilize all the information available in the transcript of records at the end of compulsory education. Table 6 presents estimates using more flexible models and evaluates to what extent grades in individual subjects matter for high school graduation. The first part of the table presents results for models allowing for independent effects of each of the subjects used to calculate our measures of cognitive and non-cognitive skills. The first column presents results for a model without fixed effects, similar to the model in column (3) in Table 5, while the second model includes cohort specific school fixed effects, similar to the model in column (5) in Table 5. Standardized values are used for all grades.[10]

[8] This is the case also for our measures of cognitive and non-cognitive skills in the present paper.

[9] The confidence intervals are small and not shown in the figure. Due to the small confidence intervals, the null hypotheses of linear effects are clearly rejected.

[10] To make the models in Table 6 comparable to each other, all models only include individuals with grade information in all of the 13 subjects, except the second Norwegian language. This reduces the sample with 1.3 percent compared to the sample in Table 5. For the first two models in Table 6, for which we can estimate the model on the same sample as in Table 5, the results are basically identical to a model using the larger sample. Regarding the second Norwegian language, about 7 percent of the students are exempted; most notably immigrants

In the model without fixed effects (column (1), the effect of Science (7.5 percentage points) is slightly larger than the effect of Mathematics (6.5 percentage points). Notice that in this conditional model the implicit scale is different from the model above since increasing the grade in Mathematics by one grade, holding the grade in Science constant, only increases our measure of cognitive skills by 0.5. Thus, the sum of the effects of Mathematics and Science in Table 6 is close to the effect of cognitive skills in Table 5. For every "non-cognitive" subject, the effect is smaller than for the cognitive subjects. Since the effects are very precisely estimated, we formally reject the hypothesis of equal effects of all four non-cognitive subjects even though the effects are not very different in numerical terms. Column (2) in Table 6 shows that taking into account potential variation in grading practice across schools and cohorts increases the effects of all grades except the grade in Mathematics which is the only of these subjects with an external written exit examination.

Columns (3) and (4) in Table 6 includes grades in all subjects. In addition to the subjects above, it includes three different grades in Norwegian language, two grades in English language, Social studies, and Religious and ethical education. The effects of both grades in English language (oral and written English) are insignificant and the effects of the three grades in Norwegian language are small. Taken together, these results suggest that language skills are not important for the probability to graduate high school. The last two subjects have significant effects, and in particular the performance in Social studies has predictive power on the probability to graduate.

Most students graduate on-time (3 or 4 years, depending on study track), and panel B in Table 7 presents results for this outcome. Compared to graduation within 5 years (Table 5 above and replicated in the first panel in the table), cognitive skills seem slightly more important and non-cognitive skills slightly less important, but the differences are small. Panel C in Table 7 shows results for the probability to graduate delayed, but within five years after compulsory education. In this case we restrict the sample to individuals not graduating on-time. Both cognitive and non-cognitive skills clearly increase the probability to graduate also in this case. The estimated effects in percentage points are smaller than the effects for graduating on-time. Increasing cognitive skills by one standard deviation increases the probability to graduate on time and delayed by 16 and 11 percentage points, respectively. However, since the share of

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and other students without Norwegian as their mother tongue. The models include a dummy variable for missing grade in this subject.

students graduating on time is much higher than the share graduating delayed, the effect on graduating delayed is largest in relative terms (the effects are 27 and 36 percent, respectively, evaluated at sample means). For both graduation on-time and graduation delayed, the bias in the effect of cognitive skills of excluding non-cognitive skills from the model is similar to the model above.[11]

The last two columns in Table 7 estimate separate effects for females and males. It is an interesting pattern that cognitive skills are relatively more important for males while non-cognitive skills are relatively more important for females.

4.2. Labor market attachments

The first cohort in our sample is 16 years of age in 2002 and we can follow these individuals to the age of 22 in 2008. In this section, we investigate two different outcomes; the share of months the individual receives welfare benefits in 2008 and whether he/she is inactive, defined as not being registered in either education or employment at October 15th 2008.

Table 8 presents the results. Regarding the probability of welfare participation, the effect of non-cognitive skills are about 4 times larger than the effect of cognitive skills, although cognitive skills has a separate negative and significant effect at 1 percent level. The results in the fixed effects specification imply that, on average, increasing non-cognitive skills by one standard deviation decreases the probability of welfare participation by 1.6 percentage points, i.e., 0.95 times the average rate of welfare participation. This is indeed a large effect, and it is highly nonlinear as shown in Figure 5. The absence of any effect when non-cognitive skills exceeds -0.5 is likely to reflect the fact that very few individuals with high non-cognitive skills receive welfare benefits.

Table 8 shows a similar pattern for the probability to be inactive as for the probability of welfare participation. However, the difference between the effects of cognitive and non-cognitive skills is smaller for inactivity. In this model, the effect of increasing

[11] For the models without school fixed effect (column 1 in Table 7), the bias in the effect of cognitive skills of excluding non-cognitive skills from the model is 43 percent for both graduation on-time and graduation delayed. For the model including school times cohort fixed effects (column 2), the bias is 46 and 48 percent, respectively.

cognitive and non-cognitive skills by one standard deviation is -3.8 and -5.1 percentage points (24 and 32 percent), respectively. These relationships are close to linear as shown in Figure 5.

The bias in effect of cognitive skills of excluding non-cognitive skills from the model is larger for these outcomes than for high school graduation (not reported in the table). We find a bias of 200-400 percent, which must be related to the finding that non-cognitive skills are much more important for labor market attachment than cognitive skills.[12]

The last part of Table 8 presents separate models for males and females. Overall, columns (3) and (4) show similar effects of both type of skills for males and females. The only case with a significant difference is that non-cognitive skills seem to be more strongly related to inactivity for females than for males.

Overall, the results show that both cognitive and non-cognitive skills are important for educational and labor market outcomes. Cognitive skills turn out as more important than non-cognitive skills with regard to education, while non-cognitive skills are most important for attachment to the labor market for young adults. Swedish evidence for males in Lindquist and Vestman (2011) suggest that non-cognitive skills are more important than cognitive skills for the probability to be attached to the labor market. It is interesting to note that we reach a similar conclusion using measures of non-cognitive and cognitive skills very different from the Swedish study. In addition, we find a similar pattern for females.

5. Intervention in cognitive skill training

Although the results above indicate that both cognitive and non-cognitive skills contribute to education and labor market outcomes, we cannot claim that the estimated effects can be given a causal interpretation. However, we can investigate the causal effect of an intervention in cognitive skill training by exploring that a random sample of students have to sit for the external exit exam in Mathematics. At

[12] For the model for the probability of welfare participation without school fixed effects (column 1 in Table 8), the effect of cognitive skills increases by 335 percent when non-cognitive skills is excluded from the model. The related bias for the model for inactivity is 175 percent. For the models with school fixed effects, the biases are 406 and 194 percent, respectively.

the end of compulsory education the year the students turn 16, about 40 percent of the students are randomly selected to sit an examination in Mathematics, while the other students sit an examination in either Norwegian language or English language. The examination subject is unknown up to a few days before the examination date. In 2002, 2003 and 2004 the students were informed 2, 7 and 5 days prior to the exam, respectively. In the latter two years the training period included a weekend and the national day.[13] The exam is carried out at the same day in all subjects and the students are well informed in advance about the procedure.[14]

The Norwegian Directorate for Education and Training prepares the exams, decides external examiners (teachers employed at different schools than the students they evaluate), and give clear instructions about randomization of students. Local authorities are responsible for the assignment of examination subjects to students. For this purpose they do not have do randomize at each schools. At small schools all students might have the same examination subject.

The findings above indicates that high school graduation is not related to skills in Norwegian and English languages, but to cognitive skills measured by grades in Mathematics and Science. Based on these results, we expect that students randomly selected to the Mathematics examination are exposed to an intensive training period that is more important for future education than students randomly selected to sit a language examination. Students selected for examination in Mathematics are randomly drawn to an intense training period in cognitive skills. Obviously, since this is an intervention in training in a short period of time, we do not expect an effect size similar to increasing cognitive skills by one standard deviation.

To estimate the impact of the intervention, we consider the following simple model, where Y_{ijc} represents the outcome of interest and the variable “intervention” equals unity if the student is selected to sit for an examination in Mathematics and zero otherwise. β can thus be interpreted as the local average treatment effect.

[13] In 2002 the students were informed about their exam subject on May 22 and they sat the exam on May 24. The relevant dates were May 15 and May 22 in 2003 and May 14 and May 19 in 2004.

[14] There are two formal written Norwegian languages. Students that are drawn to have their exam in Norwegian have two exam days, one in each language. The first exam day is simultaneous to the exam in the other subjects.

(2) $Y_{ijc} = \alpha + \beta intervention_{ic} + X_{ic}{}'\delta + \gamma_c + \varepsilon_{ic}$

While the formal system should imply that selection of students into treatment is random, we nevertheless provide some preliminary analysis of the statistical properties of those students selected for examination in Mathematics compared to the other students. Table 9 presents mean values of the individual and family characteristics for the two groups of students. None of the differences in mean values are significant at 5 % level, which suggests that the rules are actually followed. The last column in Table 9 presents results from a regression where the indicator for the intervention is the dependent variable. One of the coefficients is significant at 5 % level, but a test of joint significance cannot reject that all effects are jointly insignificant (p-value of 0.27).

Table 10 presents the main results. The intervention is estimated to increase the probability to graduate from high school within 5 years by 0.65 percentage points, which is significant at 5 percent level. The causal effect of the intervention is thus about 5 percent of the effect of a standard deviation in cognitive skills as estimated above. Notice, however, that since our measure of cognitive skills is the average grade across two subjects (Mathematics and Science), the causal effect of the intervention is about 10 percent of the effect of the grade in Mathematics. This is not a non-trivial average impact of an intensive training period of only a very few days. Since the selection into treatment is random, the estimated effect does not depend on whether the model includes socioeconomic characteristics (column 2) or not (column 1), but the effect is slightly more precisely estimated in the former case.

The OLS results above indicate that improved cognitive skills measured by grades in mathematics and science do not matter for the probability to graduate for high-ability students. To investigate whether the pattern is the same for the intervention, Figure 6 presents separate intervention effects for students at different levels of cognitive skills. The figure is based on the model including socioeconomic characteristics, but is insensitive to this choice. In accordance with OLS results, there is no effect of cognitive skill training at high skill levels. Further, the OLS findings indicate that cognitive skills have larger effects on males than females. Columns (3)-(6) in Table 10 present gender specific estimates. The effect on females turns out to be small and insignificant, while the effect on males is highly significant. To be randomly selected to sit for an external exit exam in Mathematics increases the probability to graduate from high school within 5 years for males by about one percentage point.

Table 10 shows the same pattern for graduation on time and graduating delayed as for graduating within five years, although the effects are not significant for on time graduation. This pattern might be due to the skill distribution of the samples. The effect on graduating delayed is estimated on the sample of individuals that do not graduate on time. For this sample the average cognitive skill as measured by average grade is 3.01, while it is 4.2 for those graduating on time.

Table 10 also presents results for the probability to be welfare participant and to be neither employed nor in education (inactive) at age 22. These models are restricted to the 2002-cohort when the training period was shortest. For welfare participation, the overall effect is negative as expected, and again the effect is significant at 5 percent level for males. For males the intervention is estimated to reduce the probability of being on welfare by 0.3 percentage points (18 percent). The overall effect on the probability to be inactive is positive, but close to zero. The effect on males is negative as expected, but significant only at the 20 percent level.[15] However, the effect on females is positive and marginally significant at 5 percent level.

Given positive causal effects of cognitive training, it is natural to expect that a long training period is more beneficial than a short training period. We investigate this issue by utilizing that the training period - the period from information about exam subject to the exam day – varies across cohorts. Subtracting holidays, the training period was 2, 5, and 3 days in 2002, 2003, and 2004, respectively. We have estimated models with cohort specific intervention effects. For graduating high school within five years, the average effects are 0.47, 1.11 and 0.48 percentage points in 2002, 2003, and 2004, respectively. Interestingly, the differences in effect size are closely related to the differences in training periods. The effect is clearly largest in 2003 when the training period was longest.[16]

Table 11 facilitates the interpretation by presenting results where the intervention is specified as the number of training days. We find that one day with intensive cognitive training increases the probability of graduating from high school by 0.2 percentage points on average. Due to the low precision in estimated coefficients, we cannot statistically distinguish between this model formulation and the model specification in

[15] Restricting the sample to males with average grade in Mathematics and science below 4.5 (71 percent of the males), the effect becomes larger (-0.014) and significant at 5 percent level.

[16] Notice, however, that we cannot formally reject that the effect is equal across cohorts since the effects are imprecisely estimated.

Table 10 with equal effects across cohorts. However, in a ‘horse-race’ model including both the number of training days and the dummy variable for the intervention, the estimate of the latter variable is negative, clearly indicating that the model with the number of training days gives the best description of the data. [17]

All the results in Table 11 are in accordance with the results in Table 10. One day of intensive cognitive training increase the probability to graduate on time with 0.14 percentage points and the probability to graduate delayed by 0.23 percentage points, and both effects are significant at 10 and 5 percent level, respectively. All effects are insignificant for females, while the effects on graduation within five years and graduating delayed are significant for males.

6. Concluding remarks

This paper investigates the impact of cognitive and non-cognitive skills on the propensity to graduate from high school and labor attachment for young adults. We use detailed grade transcripts from compulsory education in Norway, and measure cognitive skills by average grades in Mathematics and Science and non-cognitive skills by average grades in practical and behavioral subjects. We find that both types of skills are of roughly equal importance for the probability to graduate from high school, and that the effect sizes depends on whether the measures of both kinds of skills are included or not. The impact of cognitive skills is larger for males than for females, and the impact of non-cognitive skills is larger for females than for males. Our results further show that non-cognitive skills are substantially more important than cognitive skills for welfare participation or the probability to neither be employed nor in further education at age 22.

An important question is whether these results reflect innate ability or other invariant characteristics or whether they represent causal effects. The results might not necessarily imply that increasing the time in school on cognitive subjects and training

[17] In a model for high school graduation within five years including both the number of training days and the dummy variable for the intervention, the effect of the former variable is 0.0037 (0.0036) and the effect of the latter variable is -0.0058 (-0.0130) in the specification without socioeconomic characteristics (standard errors in parentheses). Including socioeconomic characteristics in the model changes the effects to 0.0021 (0.0026) and -0.0005 (-0.0093), respectively.

in non-cognitive skills improve outcomes. To explore this question, we estimate the causal effect of intervention in cognitive skill training by utilizing that a random sample of students have to sit for an external exit examination in Mathematics by the end of compulsory education. We find that this short and intensive training period in Mathematics increases the probability to graduate from high school. This effect is driven by males, consistent with the finding using grades that cognitive skills have a larger impact on males than on females.

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Table 1. Description of subjects in compulsory education, and descriptive statistics on grades

Subject	Description	Mean value (Std. dev.)
Mathematics		3.49 (1.12)
Science	Science and the environment	3.95 (1.11)
Physical education	Gymnastics, sports, etc.	4.35 (0.96)
Food and health (Home economics)	Food and lifestyle, food and culture, and food and consumption	4.35 (0.84)
Arts and crafts	Visual communication, design, art and architecture	4.23 (0.91)
Music	Making music, composition and listening	4.22 (0.97)
Norwegian, written		3.87 (0.97)
Second Norwegian language, written	The Norwegian language contains of two different languages. This is their second choice	3.64 (1.00)
Norwegian, oral		4.07 (0.98)
English, written		3.75 (1.07)
English, oral		4.02 (0.99)
Religious and ethical education	Christianity, other religions and philosophies of life. Philosophy and ethics.	4.01 (1.10)
Social studies	History, geography, government, economics, and civics	4.06 (1.08)

Table 2. Data reduction

	Observations	Percent
Finish compulsory education in 2002-2004	174,067	100.0
Not turning 16 years the year finishing compulsory education	10,059	5.8
Missing grade information*	8,883	5.1
Missing compulsory school identifier	610	0.4
Analytical sample	154,515	88.8

* Missing information for at least one of the six subjects used to calculated our measures of cognitive and non-cognitive skills.

Table 3: Descriptive statistics for high school graduation

Cohort	Observations	On-time graduation, percent	Graduating delayed but within 5 years, percent	Not graduating within 5 years, percent
2002	49,056	57.3	13.4	29.2
2003	50,884	56.8	13.7	29.4
2004	54,575	57.0	14.2	28.8
Total	154,515	57.1	13.8	29.2

Table 4: Descriptive statistics on labor market outcomes, 2002-cohort

	All observations	Graduated high school within five years	Not graduated high school within five years
Share of months on welfare in 2008, percent	1.7	0.3	4.9
Inactive October 15th 2008, percent	15.9	9.9	30.5
Observations	49,056	34,715	14,341

Table 5. The effects of skills on high school graduation within 5 years

	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive skills	0.143**	0.132**	0.194**	0.129**	0.130**	0.132**
	(0.0019)	(0.0019)	(0.0013)	(0.0018)	(0.0017)	(0.0018)
Non-cognitive skills	0.117**	0.106**	-	0.116**	0.117**	0.115**
	(0.0018)	(0.00185)		(0.00173)	(0.00170)	(0.00182)
Socioeconomic characteristics	No	Yes	Yes	Yes	Yes	Yes
School FE (no of groups)	0	0	0	1,186	-	-
Cohort x school FE (no of groups)	0	0	0	0	3,349	-
Cohort x ward FE (no of groups)	0	0	0	0	0	32,319
R-squared	0.285	0.300	0.277	0.297	0.299	0.289
Observations	154,515	154,515	154,515	154,515	154,515	154,447

Note. Standard errors in parentheses are clustered by compulsory school, * and ** denote significance at 5 and 1 percent level, respectively.

Table 6. Subject specific effects. Dependent variable is graduation from high school within 5 years

	(1)	(2)	(3)	(4)
Mathematics	0.0647**	0.0578**	0.0458**	0.0393**
	(0.00186)	(0.00187)	(0.00187)	(0.00188)
Science	0.0753**	0.0811**	0.0408**	0.0451**
	(0.00209)	(0.00200)	(0.00226)	(0.00219)
Physical education	0.0428**	0.0443**	0.0351**	0.0367**
	(0.00148)	(0.00143)	(0.00146)	(0.00142)
Food and health (Home economics)	0.0262**	0.0315**	0.0190**	0.0236**
	(0.00171)	(0.00152)	(0.00170)	(0.00152)
Arts and crafts	0.0339**	0.0373**	0.0274**	0.0308**
	(0.00164)	(0.00158)	(0.00163)	(0.00157)
Music	0.0319**	0.0348**	0.0172**	0.0194**
	(0.00178)	(0.00166)	(0.00181)	(0.00168)
Norwegian, written	-	-	0.00613**	0.00927**
			(0.00209)	(0.00202)
Second Norwegian language, written	-	-	0.00127	-0.00233
			(0.00188)	(0.00181)
Norwegian, oral			0.0159**	0.0168**
			(0.00203)	(0.00201)
English, written	-	-	-0.00294	-0.00332
			(0.00205)	(0.00204)
English, oral	-	-	-1.52e-05	-0.000894
			(0.00198)	(0.00198)
Religious and ethical education	-	-	0.0307**	0.0323**
			(0.00225)	(0.00218)
Social studies	-	-	0.0436**	0.0441**
			(0.00211)	(0.00201)
Socioeconomic characteristics	Yes	Yes	Yes	Yes
Cohort x school FE (no of groups)	0	3,340	0	3,340
R-squared	0.295	0.295	0.305	0.304
Observations	152,468	152,468	152,468	152,468

Note. Same model specification as in columns (2) and (4) in Table 6 except as indicated. In all models the sample is restricted to individuals with grade information in all the 13 subjects, except the second Norwegian language for which the model include an indicator for missing value (see footnote 10). Standard errors in parentheses are clustered at the school level. * and ** denote significance at 5 and 1 percent level, respectively.

Table 7. The effect of skills on high school graduation

	(1)	(2)	(3)	(4)
Sample	All	All	Females	Males
A. Graduation within 5 years				
Cognitive skills	0.132**	0.130**	0.114**	0.144**
	(0.00192)	(0.00171)	(0.0024)	(0.0023)
Non-cognitive skills	0.106**	0.117**	0.128**	0.110**
	(0.00185)	(0.00170)	(0.0025)	(0.0023)
Observations	154,515	154,515	75,778	78,737
B. On-time graduation				
Cognitive skills	0.156**	0.157**	0.145**	0.165**
	(0.0019)	(0.0018)	(0.0026)	(0.0024)
Non-cognitive skills	0.097**	0.106**	0.125**	0.094**
	(0.0020)	(0.0018)	(0.0027)	(0.0024)
Observations	154,515	154,515	75,778	78,737
C. Delayed graduation, but within 5 years				
Cognitive skills	0.110**	0.112**	0.099**	0.121**
	(0.0030)	(0.0029)	(0.0050)	(0.0037)
Non-cognitive skills	0.064**	0.073**	0.070**	0.075**
	(0.0024)	(0.0025)	(0.0042)	(0.0032)
Observations	66,348	66,348	26,877	39,471
Socioeconomic characteristics	Yes	Yes	Yes	Yes
Cohort x school FE	No	Yes	Yes	Yes

Note. The same socioeconomic characteristics as in the models in Table 5 are included. Standard errors in parentheses are clustered at the school level, * and ** denote significance at 5 and 1 percent level, respectively.

Table 8. The effect of skills on lack of labor market attachment at age 22, 2002-cohort

	(1)	(2)	(3)	(4)
Sample	All	All	Females	Males
On welfare				
Cognitive skills	-0.0043**	-0.0036**	-0.0031**	-0.0039**
	(0.0007)	(0.0007)	(0.0010)	(0.0010)
Non-cognitive skills	-0.0144**	-0.0157**	-0.0171**	-0.0151**
	(0.0010)	(0.0010)	(0.0015)	(0.0014)
Inactive				
Cognitive skills	-0.0406**	-0.0376**	-0.0398**	-0.0342**
	(0.0025)	(0.0026)	(0.0041)	(0.0035)
Non-cognitive skills	-0.0433**	-0.0506**	-0.0592**	-0.0452**
	(0.0028)	(0.0029)	(0.0047)	(0.0038)
Observations	49,056	49,056	23,860	25,196
Socioeconomic characteristics	Yes	Yes	Yes	Yes
School fixed effects	No	Yes	Yes	Yes

Note. The same socioeconomic characteristics as in the models in Table 5 are included. Standard errors in parentheses are clustered at the school level, * and ** denote significance at 5 and 1 percent level, respectively.

Table 9: Intervention in cognitive training, balanced sample

	Mean values		Difference	OLS on the intervention
	Intervention	No intervention		
Cognitive skills	-0.004	0.002	-0.0059	-0.0067
			(0.0089)	(0.00389)
Non-cognitive skills	0.006	-0.004	0.0098	0.0084
			(0.0106)	(0.00456)
Female	0.490	0.491	-0.0004	-0.0031
			(0.00267)	(0.00295)
First generation immigrant	0.032	0.033	-0.0003	0.0014
			(0.00157)	(0.01364)
Second generation immigrant	0.021	0.020	0.0004	0.0063
			(0.00199)	(0.02382)
Parents’ highest educational level	0.471	0.466	0.0052	0.0033
is high school education			(0.00429)	(0.00444)
Parents’ highest educational level	0.288	0.290	-0.0014	0.0010
is bachelor degree			(0.00281)	(0.00550)
Parents’ highest educational level	0.101	0.104	-0.0028	-0.0002
is master or PhD			(0.00331)	(0.00873)
Benefits due to disease before	0.018	0.019	-0.0010	-0.0107
the age of 18			(0.00072)	(0.01091)
Benefits due to disabilities before	0.023	0.024	-0.0009	-0.0031
the age of 18			(0.00081)	(0.00924)
One parent employed	0.237	0.241	-0.0042	0.0045
			(0.00277)	(0.00675)
Both parents employed	0.712	0.707	0.0053	0.0138
			(0.00346)	(0.00762)
Parental income in 100,000 NOK	6.005	6.077	-0.0716	-0.0017*
			(0.0436)	(0.00077)
Parental income in 100 NOK squared	49.149	54.577	-5.428	0.0000
			(4.368)	(0.00000)
Married parents	0.616	0.612	0.0046	0.0023
			(0.00318)	(0.00402)
Divorced parents	0.123	0.126	-0.0027	-0.0035
			(0.00183)	(0.00472)
Mobility	0.111	0.109	0.0014	0.0061
			(0.00214)	(0.00540)
Mobility unknown	0.020	0.020	-0.0008	-0.0059
			(0.00085)	(0.01095)
Born second quartile	0.265	0.268	-0.0025	-0.0034
			(0.0024)	(0.00354)
Born third quartile	0.258	0.259	-0.0015	-0.0024
			(0.00235)	(0.00354)
Born fourth quartile	0.230	0.227	0.0028	0.0022
			(0.00229)	(0.00353)
Cohort 2003	0.329	0.330	-0.0013	-0.0117
			(0.02535)	(0.03122)
Cohort 2004	0.345	0.358	-0.0133	-0.0196
			(0.02322)	(0.02753)
Observations	60,138	94,377	154,515	154,515

Note. Std. errors in parentheses are clustered at the school level, * and ** denote significance at 5 and 1 percent level, respectively.

Table 10. Effects of intervention in cognitive training

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	All		Females		Males	
High school graduation within 5 years	0.0065*	0.0066*	0.0019	0.0026	0.0109*	0.0104**
	(0.0033)	(0.0026)	(0.0038)	(0.0033)	(0.0043)	(0.0036)
Observations	154,515	154,515	75,778	75,778	78,737	78,737
High school graduation on time	0.0041	0.0045	0.0002	0.0011	0.0080	0.0076
	(0.0037)	(0.0029)	(0.0044)	(0.0038)	(0.0049)	(0.0041)
Observations	154,515	154,515	75,778	75,778	78,737	78,737
Delayed high school graduation, but within 5 years	0.0087*	0.0081*	0.0051	0.0053	0.0112*	0.0101*
	(0.0041)	(0.0038)	(0.0060)	(0.0057)	(0.0052)	(0.0048)
Observations	66,348	66,348	26,877	26,877	39,471	39,471
On welfare at age 22, 2002-cohort	-0.0010	-0.0010	0.0009	0.0009	-0.0029*	-0.0029*
	(0.0011)	(0.0010)	(0.0014)	(0.0013)	(0.0015)	(0.0014)
Observations	49,056	49,056	23,860	23,860	25,196	25,196
Inactive at age 22, 2002-cohort	0.0011	0.0012	0.0101	0.0097*	-0.0076	-0.0069
	(0.0039)	(0.0035)	(0.0053)	(0.0049)	(0.0054)	(0.0051)
Observations	49,056	49,056	23,860	23,860	25,196	25,196
Socioeconomic characteristics	No	Yes	No	Yes	No	Yes
Cohort specific effects	No	Yes	No	Yes	No	Yes

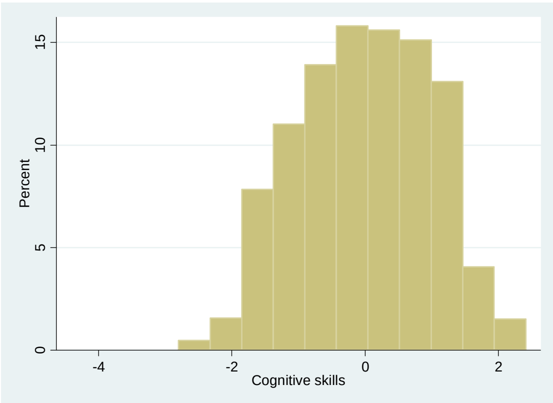
Note. Each cell represents an independent regression. The same socioeconomic characteristics as in the models in Table 5 are included. Standard errors in parentheses are clustered at the school level, * and ** denote significance at 5 and 1 percent level, respectively.

Table 11. Effects of intervention duration

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	All		Females		Males	
High school graduation within 5 years	0.0022*	0.0020**	0.0012	0.0013	0.0031**	0.0027**
	(0.0009)	(0.0007)	(0.0011)	(0.0009)	(0.0012)	(0.0010)
Observations	154,515	154,515	75,778	75,778	78,737	78,737
High school graduation on time	0.0015	0.0014	0.0008	0.0009	0.0021	0.0018
	(0.0010)	(0.0008)	(0.0013)	(0.0011)	(0.0013)	(0.0011)
Observations	154,515	154,515	75,778	75,778	78,737	78,737
Delayed high school graduation, but within 5 years	0.0027*	0.0023*	0.0018	0.0018	0.0033*	0.0027
	(0.0011)	(0.0011)	(0.0017)	(0.0016)	(0.0015)	(0.0014)
Observations	66,348	66,348	26,877	26,877	39,471	39,471
Socioeconomic characteristics	No	Yes	No	Yes	No	Yes
Cohort specific effects	Yes	Yes	Yes	Yes	Yes	Yes

Note. Each cell represents an independent regression. The same socioeconomic characteristics as in the models in Table 5 are included. Standard errors in parentheses are clustered at the school level, * and ** denote significance at 5 and 1 percent level, respectively.

Figure 1. The distribution of cognitive and non-cognitive skills



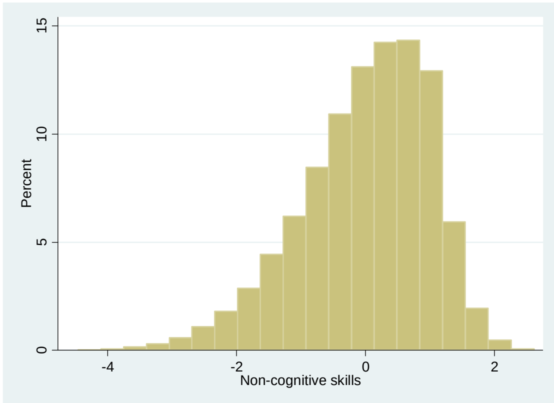
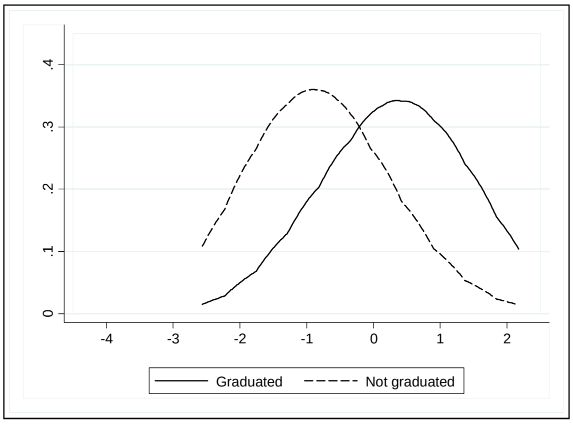
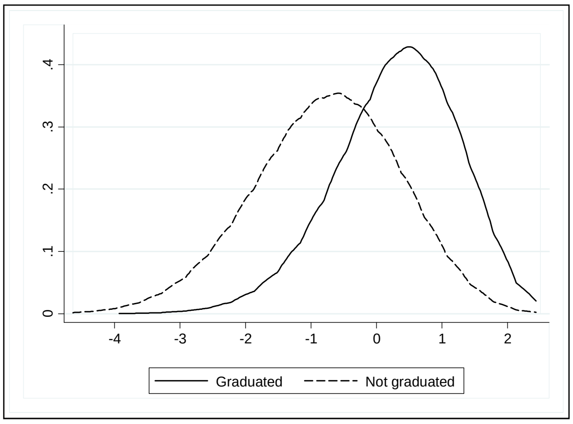


Figure 2. Graduation within five years and skills

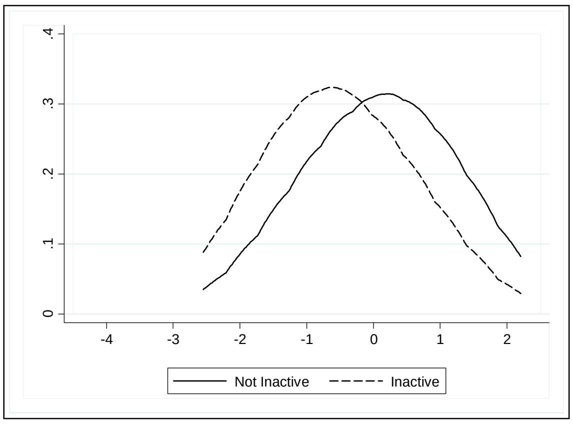


Panel A. Cognitive skills

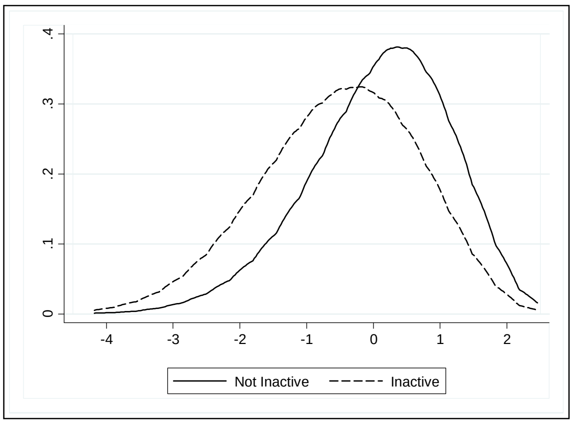


Panel B. Noncognitive skills

Figure 3. Inactivity and skills



Panel A. Cognitive skills



Panel B. Noncognitive skills

Figure 4. Non-parametric effects of skills on high school graduation

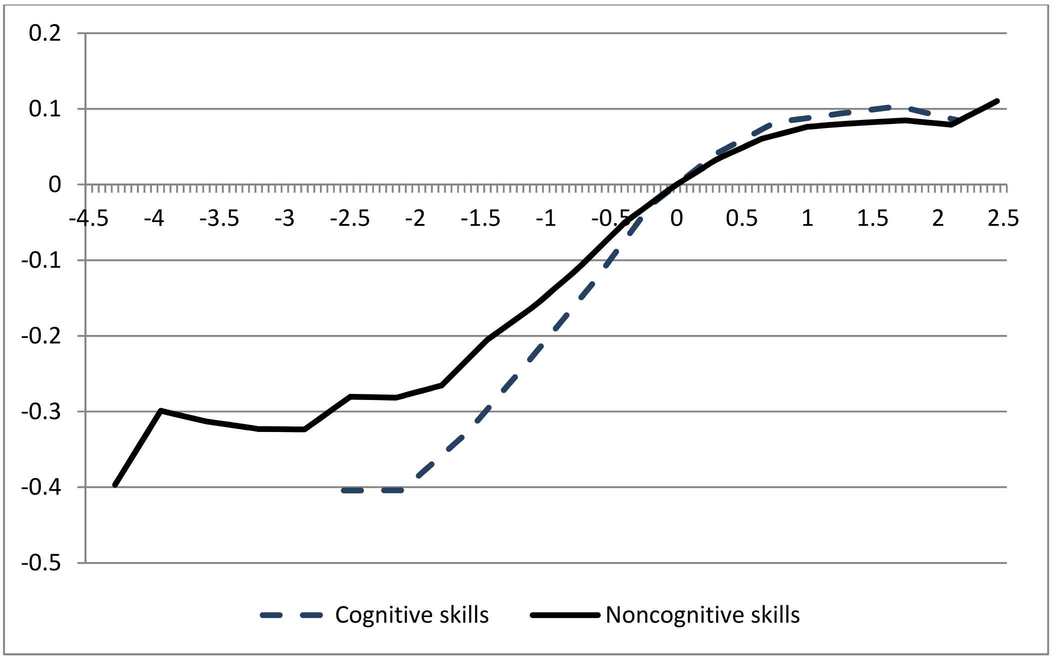
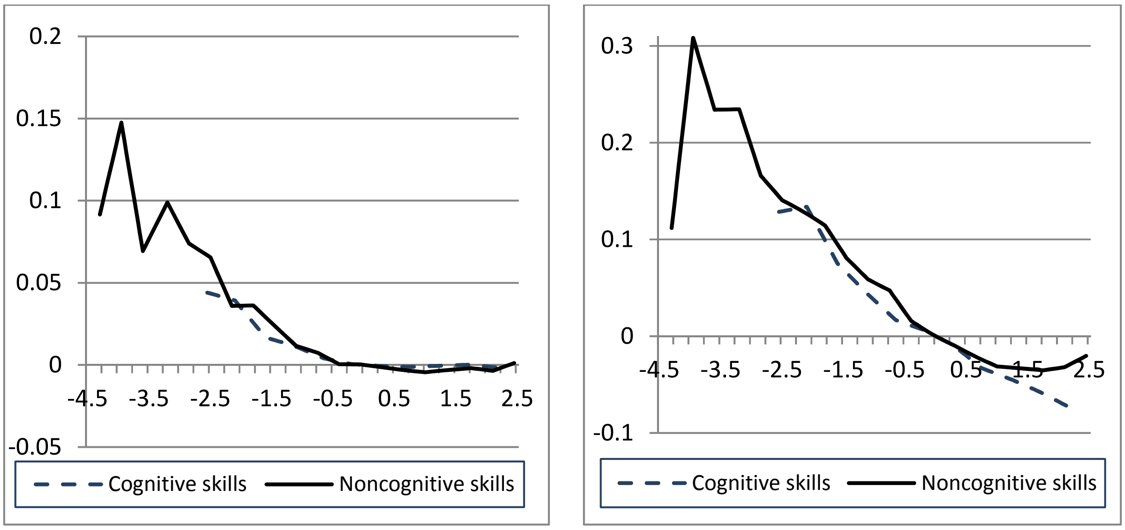


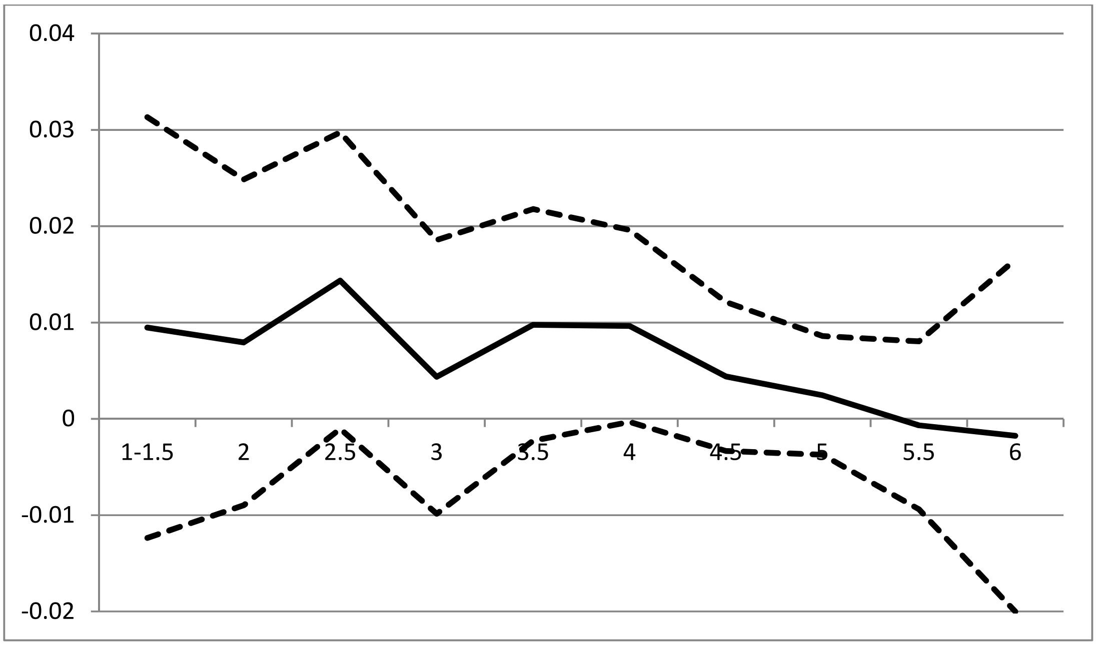
Figure 5. Non-parametric effects of skills on being on welfare and inactive



Panel A: On welfare

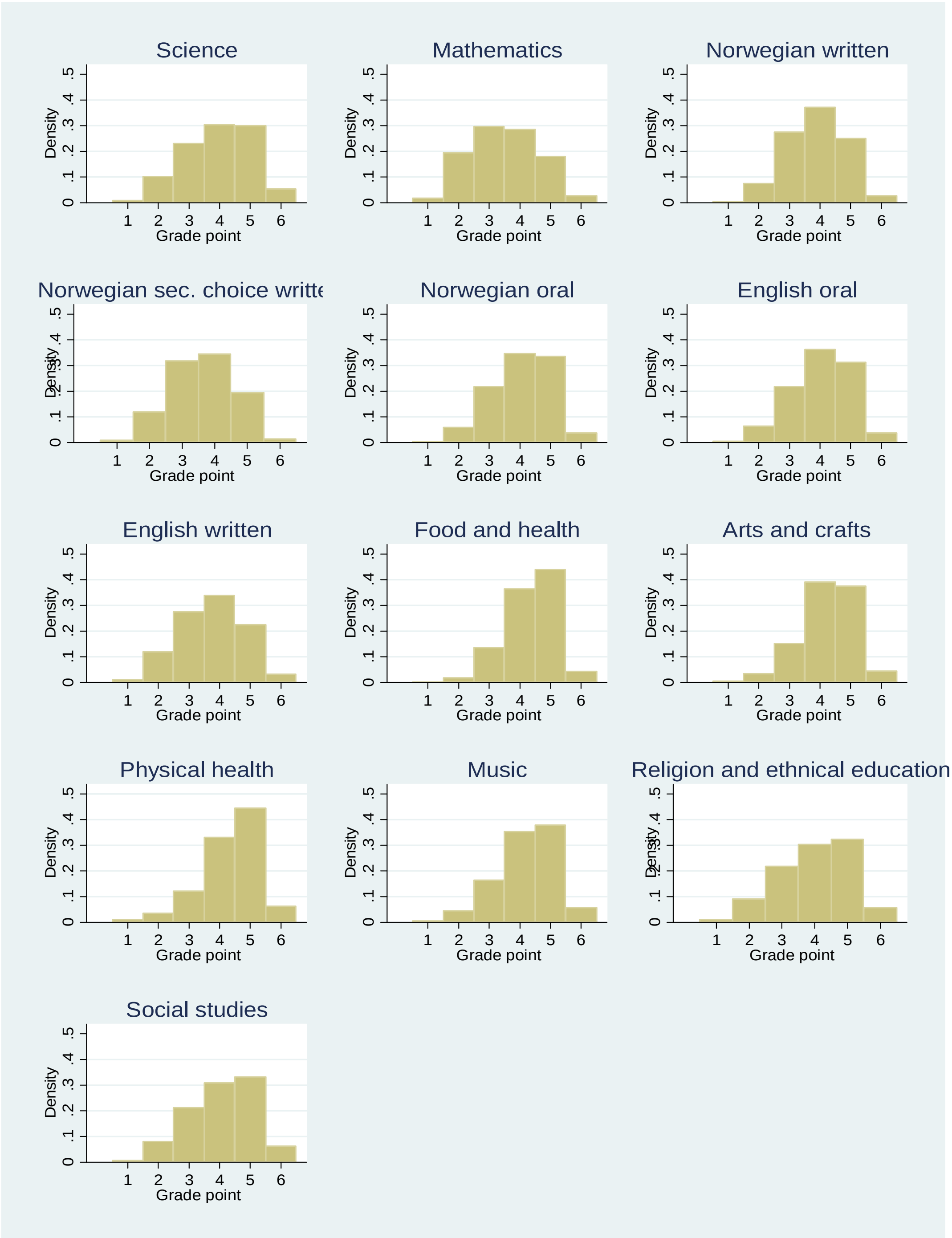
Panel B: Inactive

Figure 6. The effect of the intervention on the probability to graduate high school within 5 years at different levels of cognitive skills, 95% confidence intervals



Appendix

Figure A1: The distribution of assessed attainment in all subjects



Appendix Table A1. Descriptive statistics for independent variables

	2002-2004 cohort	2002-cohort
Cognitive skills	0.00 (1.00)	-0.02 (1.00)
Non-cognitive skills	0.00 (1.00)	-0.05 (1.01)
Female	0.49	0.49
First generation immigrant	0.03	0.03
Second generation immigrant	0.02	0.02
Parents' highest educational level is high school education	0.47	0.47
Parents' highest educational level is bachelor degree	0.29	0.28
Parents' highest educational level is master or PhD	0.1	0.1
Benefits due to disease before the age of 18	0.02	0.02
Benefits due to disabilities before the age of 18	0.02	0.02
One parent employed	0.24	0.23
Both parents employed	0.71	0.72
Parental income in 100,000 NOK	6.05 (3.98)	5.87 (4.55)
Married parents	0.61	0.64
Divorced parents	0.12	0.12
Mobility	0.11	0.11
Mobility unknown	0.02	0.02
Born second quartile	0.27	0.27
Born third quartile	0.26	0.26
Born fourth quartile	0.23	0.23
Observations	154,515	49,056

Note. Standard deviations in parentheses.

Appendix Table A2. Fully specified models

	(1) Graduation	(2) On-time	(3) Delayed	(4) On welfare	(5) Inactive
Cognitive skills	0.130**	0.157**	0.112**	-0.00359**	-0.0376**
	(0.00171)	(0.00184)	(0.00305)	(0.000717)	(0.00262)
Non-cognitive skills	0.117**	0.106**	0.0730**	-0.0157**	-0.0506**
	(0.00170)	(0.00183)	(0.00251)	(0.00101)	(0.00293)
Female	0.00587**	0.0595**	-0.0419**	0.00768**	0.0198**
	(0.00226)	(0.00262)	(0.00395)	(0.000956)	(0.00376)
First generation immigrant	0.0454**	0.0418**	0.0285**	-0.0150**	0.0111
	(0.00723)	(0.00717)	(0.0109)	(0.00325)	(0.0133)
Second generation immigrant	0.0515**	0.0380**	0.0351**	-0.0159**	-0.0352*
	(0.00825)	(0.00924)	(0.0126)	(0.00280)	(0.0140)
Parents' highest educational level is	0.0437**	0.0253**	0.0248**	-0.0112**	-0.0270**
high school education	(0.00358)	(0.00339)	(0.00452)	(0.00207)	(0.00631)
Parents' highest educational level is	0.0577**	0.0491**	0.0462**	-0.00842**	-0.0257**
bachelor degree	(0.00385)	(0.00393)	(0.00574)	(0.00206)	(0.00678)
Parents' highest educational level is	0.0418**	0.0432**	0.0541**	-0.00561**	-0.0306**
master or PhD	(0.00452)	(0.00511)	(0.00993)	(0.00213)	(0.00790)
Benefits due to disease before the	0.0108	0.0106	0.0130	0.00146	0.0225
age of 18	(0.00835)	(0.00916)	(0.0120)	(0.00544)	(0.0166)
Benefits due to disabilities before the	-0.0557**	-0.0444**	-0.0359**	0.0134*	0.0683**
age of 18	(0.00774)	(0.00822)	(0.00987)	(0.00575)	(0.0160)
One parent employed	0.0399**	0.0295**	0.00922	-0.0156**	-0.0247*
	(0.00546)	(0.00546)	(0.00679)	(0.00398)	(0.00992)
Both parents employed	0.0706**	0.0565**	0.0333**	-0.0243**	-0.0558**
	(0.00555)	(0.00553)	(0.00731)	(0.00384)	(0.0102)
Parental income in 100,000 NOK	0.00120**	0.00181**	0.00271**	-0.00043**	-0.000223
	(0.000328)	(0.000427)	(0.000930)	(0.000114)	(0.000549)
Parental income in 100 NOK squared	-0.0023**	-3.01e-06**	-3.41e-05**	7.74e-07**	-1.98e-07
	(7.72e-07)	(8.53e-07)	(9.37e-06)	(1.99e-07)	(9.15e-07)
Married parents	0.0511**	0.0431**	0.0556**	-0.0105**	-0.0181**
	(0.00262)	(0.00277)	(0.00429)	(0.00128)	(0.00445)
Divorced parents	0.00619	-0.00107	0.00823	-0.00123	-0.00199
	(0.00349)	(0.00359)	(0.00526)	(0.00200)	(0.00620)
Mobility	-0.0439**	-0.0320**	-0.0399**	0.0153**	0.0304**
	(0.00344)	(0.00352)	(0.00479)	(0.00217)	(0.00578)
Mobility unknown	-0.00931	-0.0133	-0.00330	0.000123	0.0229
	(0.00879)	(0.00936)	(0.0131)	(0.00390)	(0.0150)
Born second quartile	0.00912**	0.0131**	0.000787	-0.000725	-0.0104*
	(0.00268)	(0.00278)	(0.00486)	(0.00120)	(0.00482)
Born third quartile	0.0228**	0.0245**	0.0138**	-0.00232*	-0.00724
	(0.00274)	(0.00290)	(0.00489)	(0.00117)	(0.00478)
Born fourth quartile	0.0297**	0.0290**	0.0182**	-0.00157	-0.0141**
	(0.00289)	(0.00309)	(0.00507)	(0.00128)	(0.00498)
Observations	154,515	154,515	66,348	49,056	49,056
R-squared	0.299	0.295	0.138	0.061	0.066
Cohort x school FE (no of groups)	3,349	3,349	3,266	1,124	1,124

Note. Standard errors in parentheses are clustered by compulsory school, * and ** denote significance at 5 and 1 percent level, respectively.