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Performance of Young Adults: The Importance of Different Skills

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Abstract

This article uses teacher assessments at age 16 in Norwegian comprehensive schools to estimate the relationship between different types of skills and performance of young adults. While we follow the literature and consider grades in Mathematics and Science as proxy for cognitive skills, we use a novel measure for another type of skills; performance in behavioral and practical subjects. Using individual register data, we find that both types of skills are important predictors of high school graduation. For longer term outcomes, we find that non-cognitive skills is the most important predictor of the probability to receive welfare benefits at age 22, whereas cognitive skills is most important for the probability to start college. (JEL codes: I21, J24)

Keywords: skills, grades, high school graduation, NEET, welfare benefits

1 Introduction

A number of studies in economics have found that students' 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, such measures can indirectly also capture 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).

Although the evidence suggests that earnings are positively related to both non-cognitive and cognitive skills, the relationship might vary across the earnings distribution. Recent evidence by Lindquist and Vestman (2011) indicates that non-cognitive (cognitive) skills measured at the Swedish military draft are most important in the lower (upper) part of the male earnings distribution. One limitation of military draft data, at age 18–19, is that skills are measured after post-compulsory educational choices are made. Thus the skill measures might to some extent reflect

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differences in schooling,[1] and the data do not allow direct studies of the relationship between high school graduation and skills.

This article contributes to the literature by providing estimates of the relationship between different kinds of skills measured at the end of compulsory education in Norway (age 16) and performance of young adults. We distinguish between two sets of skills that are regarded as important by the school system and evaluated objectively by teachers: achievement in Mathematics and Science and achievement in 'behavioral and practical' subjects such as Arts and crafts and Physical education. In line with most other studies in the economics literature on the effect of skills, we consider achievement in Mathematics and Science as a measure of cognitive skills. For the other group of subjects, teacher assessed grades arguably reflect student characteristics such as conscientiousness and openness to experience to a larger extent than other subjects. For example, teacher assessed grades in Physical education reflects engagement, preferences for following rules, motivation, and ability to show up on-time rather than just particular performance in sports. Although there are obvious conceptual issues, we consider the grades in behavioral and practical subjects as proxy for non-cognitive skills throughout the article.[2] For the interpretation, it would be interesting to provide evidence on the relationship between our skill measures and traditional measures of cognitive skills (typically IQ) and non-cognitive skills (typically survey-based information), but such information is to the best of our knowledge not available.

Although the empirical models include a rich set of individual characteristics and the empirical results seem robust to model specification, the findings cannot readily be interpreted causally in the sense that an intervention increasing these skills has the same impact. This is a weakness our analysis shares with the literature on cognitive and non-cognitive skills in general. Since the skill variables are correlated, we provide estimates of the lower and upper bounds of the correlations between outcomes and the different types of skills.

In the literature, measures of non-cognitive skills are mainly based on self-reported survey data. The reliance on self-reported information, combined with inherent difficulties in distinguishing conceptually between cognitive and non-cognitive skills, suggests that evidence based on other types of data can enhance the understanding of the role of different types of skill. An advantage of our analysis is that skills are evaluated by persons

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[1] Several authors find that traditional cognitive skill measures (IQ) is partly determined by education, see Falch and Massih (2011) and the references therein.

[2] Alternatively, the analysis can be seen as relating grades in two different groups of subjects to the performance of young adults.

external to the students. We use detailed grade information from transcript of records at the end of compulsory education at age 16 in Norway. This is a comprehensive school system in the sense that all students have the same subjects and common curriculum. The fact that our skill measures are obtained before any schooling decision is made by the student is an advantage compared to the measures used in Lindquist and Vestman. While their data naturally is restricted to men, a further advantage is that our data include the total student population and allow us to investigate if the relative importance of different skill types differs by gender.

We relate the skill measures to high school graduation, college enrollment, labor market attachment, and the probability to receive welfare benefits for young adults using register data for the cohorts leaving compulsory education in Norway in 2002–2004. We find that graduation from high school is strongly associated with both types of skills. 'Non-cognitive' skills is the most important predictor of the probability to receive welfare benefits at age 22, whereas 'cognitive' skills are most important for college enrollment. The results are robust to the inclusion of different sets of school and neighborhood fixed effects.

The article is organized as follows: Section 2 reviews related literature. Section 3 presents relevant institutional settings in Norway, the data, and the empirical specification. Empirical results are reported in Section 4, while Section 5 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 relationship between such skills measured by test scores in Mathematics and Science and earnings and to some extent also other individual outcomes. To take a few representative studies; Bishop (1989), Murnane et al. (1995), and Altonji and Pierret (2001) all find that achievement measures are important predictors 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 mathematical 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) all find that cognitive skills as measured by aggregate scores on international comparable student tests in Mathematics and Science are strongly related to economic growth.

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The literature on the role of cognitive skills has been challenged by authors arguing that some of the associations with cognitive skills in reality capture 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) finds that personal traits as leadership, industriousness, and perseverance are strongly related to 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. Heckman and Rubinstein (2001) provide an instructive example of the potential role played by non-cognitive skills. 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 worse outcomes than high school dropouts, holding cognitive skills constant. Heckman et al. (2006) use US national Longitudinal Survey of Youth (NLSY) to estimate the relationship between different skills and 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 and wages. Carneiro et al. (2007) find similar results for the 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) exploit that data from the Swedish military enlistment include a measure of non-cognitive skills based on an evaluation conducted by psychologists using individual interviews. They find that whereas cognitive skills measured by an IQ test 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 USA and studies the relationship between premarket teacher reported student misbehavior in eight grade

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(tardiness, absence, disruptiveness, etc.) and male labor market outcomes and the probability to obtain 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 consistent with the findings in Lindquist and Vestman (2011) on the relationship between earnings and different types of skills.

Lindquist and Vestman (2011) and Segal (2011) consider the relationship between outcomes and cognitive and non-cognitive skills only for males. Our data include the total student population, and allow us to investigate whether the relationships differ by gender.

Our study is also related to the literature on the association between participation in physical activity and sports and individual outcomes, e.g., 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. In the literature on returns to physical fitness it is typically attributed to non-cognitive skills.

3 Institutions, data, and empirical specification

3.1 Institutions

The Norwegian school system consists of 10 compulsory years. Students are normally enrolled the year they turn 6 years, and there is no possibility to fail a class. All students finish compulsory education 10 years after enrollment. It is a comprehensive school system with no tracking and a common curriculum for all students.

At graduation the students receive a diploma containing the different grades set by teachers and exam results, although for some of the weakest students grades may be missing in some subjects. Table 1 gives an overview of the relevant 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, but with largest weight on the latest tests and performance. They shall at the outset reflect skills and not effort. Thus, in subjects such as Mathematics and Science, the grades are to a large extent based on written tests conducted within the school year. Regarding other subjects, such as 'behavioral and practical' subjects,

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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)

casual evidence (e.g., Prøitz and Borgen 2010) clearly indicates that effort and behavior matter for grading in addition to skills.

After the end of compulsory education, students can choose to leave school or to enroll in high school education. High school education consists of 15 different study tracks. Three of the study tracks qualify for higher education (academic tracks) and 12 study tracks give a certificate for work in a broad amount of occupations (vocational tracks). The academic tracks consist of 3 years, while the vocational study tracks normally consist of 2 years in school plus 2 years as apprentice.

Students have a legal right to five consecutive years of high school education after finishing compulsory school, and the government uses graduation within 5 years as the measure of the graduation rate in official statistics. Therefore, we use a 5-year window in the empirical study of high school graduation below.

About 95% of the cohorts 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 the actual study track and school they enroll into depends on achievement in compulsory education measured by their average grade. Despite the high initial enrollment rate, only around 70% of each cohort graduate within 5 years. A large fraction of students drop out of high school education, which clearly is an important political concern.

Public schools have a common curriculum and the same number of teaching hours in each subject.[3] The 430 municipalities are responsible

[3] Few students enroll in private schools. About 2 and 5% of a cohort enroll in private compulsory schools and high schools, respectively.

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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% on education. Enrollment into compulsory schools is based on catchment areas, while the counties have major leeway on enrollment rules for 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.

3.2 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% of the population, amounting to 154,515 observations.

We apply the teacher assessed grades to classify two different measures of skills. Following the economics literature, we denote the average grade in Science and Mathematics as ‘cognitive’ skills. In ‘practical and behavioral’ subjects, traits as conscientiousness, openness to experience, engagement, and motivation are valued. We calculate the average of the grades in the subjects Food and health, Arts and crafts, Physical education, and Music, and for simplicity we denote this variable ‘non-cognitive’ skills.[5]

Mean values and standard deviations for the subjects are presented in Table 1. The average grade is lowest in Mathematics and highest in Physical education. While 23% of the students obtain grade 1 or 2 in

[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 1 year. It is also possible to start 1 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 our skill measures is 0.74, which clearly indicates that there are some common characteristics important for performance in both classes of skill. An alternative classification of skills could be based on a principal component analysis. However, in our view, relying on averages of observable skill measures regarded as important by the school system makes interpretation easier than using measures based on a purely data-based principal component analyses. In addition, by this approach our results are comparable to previous studies on the impact of cognitive skills.

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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[a]	8,883	5.1
Missing compulsory school identifier	610	0.4
Analytical sample	154,515	88.8

[a]Missing information for at least one of the six subjects used to calculate our measures of cognitive and non-cognitive skills.

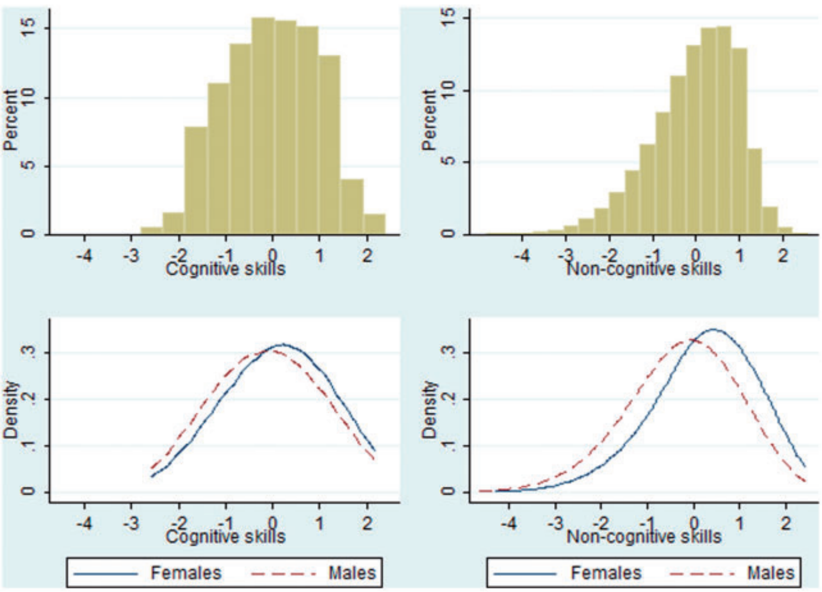

Figure 1 The distribution of cognitive and non-cognitive skills.

Mathematics, that is the case for <6% in Physical education, Food and health, Arts and craft, and Music. Thus, 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 facilitate interpretation, 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

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Table 3. Descriptive statistics for high school graduation and labor market attachment

	2002	2003	2004	All	Females	Males
Graduating within 5 years (%)	70.8	70.6	71.2	70.8	75.6	66.3
On-time graduation (%)	57.3	56.8	57.0	57.1	64.5	49.9
Graduating delayed but within 5 years (%)	13.4	13.7	14.2	13.8	11.0	16.4
Enrolled in higher education at age 21 (%)	36.5	36.6	37.8	37.0	45.8	28.5
NEET October 15th at age 22 (%)	15.9	16.7	–	16.3	15.1	17.4
Share of month on welfare at age 22 (%)	1.66	2.01	2.11	1.93	1.81	2.05
Observations	49,056	50,884	54,575	154,515	75,778	78,737

mean.[6] The lower part of Figure 1 present separate distributions for females and males. Measured by grades, the distributions of skills for females are to the right of the distributions for males, and the difference is most pronounced for 'non-cognitive' skills.[7]

Table 3 gives a description of educational and labor market outcomes. About 57% graduate within expected time, while additionally about 14% graduate delayed but within 5 years after the end of compulsory education. There are only small differences across the cohorts. Figure 2 present the distribution of skills for graduates and dropouts. Panel A shows that the distribution of 'cognitive' skills for individuals that graduate high school within 5 years is clearly to the right of the distribution for dropouts. Panel B shows a similar picture for 'non-cognitive' skills.[8]

We measure enrollment in higher education in the fall 5 years after the individuals' finished compulsory education. Since the expected time to graduate high school in an academic track that qualify for higher education is 3 years, the individuals might do military services or other activities

[6] Since the distribution of our measure of 'non-cognitive' skills is skewed to the left, the standardization might in principle affect the estimated effects. We show below that this is not the case in the present analysis.

[7] The skill variables are discrete, but the presentation of the distributions in the lower part of Figure 1 and Figures 2 and 3 below is smoothed by the choice of bandwidth. Mean values of standardized 'cognitive' skills are equal to 0.11 and –0.11 for females and males, respectively. The corresponding numbers for 'non-cognitive' skills are 0.25 and –0.24.

[8] Mean values of standardized 'cognitive' skills are 0.32 and –0.79 for graduates and dropouts, respectively. The corresponding numbers for 'non-cognitive' skills are 0.31 and –0.76.

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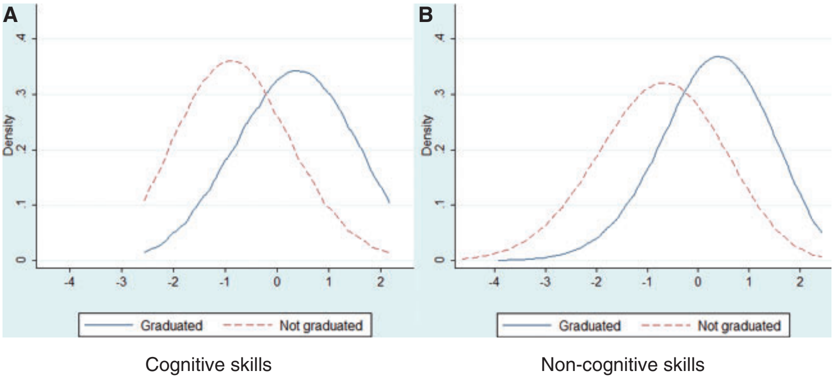

Figure 2 Graduation within 5 years and skills.

between graduating high school and our measure of higher education participation. Table 3 shows that the enrollment share in higher education at age 21 is slightly increasing in the empirical period and is on average 37%.

Regarding labor market attachment, we follow the students up to age 22. Since employment is registered on a daily basis, we measure inactivity on a specific day (October 15th). Inactivity is defined as not registered in employment, education, or training (NEET).[9] Table 3 shows that 16.3% is NEET this day. The distributions of skills for both inactive and active individuals are presented in Figure 3, which shows the same pattern as in Figure 2. The distribution of both types of skills for non-NEET individuals is clearly to the right of the distribution for NEET individuals.

In addition to the inactivity outcome, we study the probability of receiving welfare benefits. We utilize information on the number of months receiving benefits during the calendar year and use the share of the months with benefits in the analysis. Table 3 shows that on average 1.9% are on welfare in a random month the year they turn 22. During this year, about 5% of the sample receives welfare benefits at least 1 month.[10]

The last two columns in Table 3 present mean values of the outcome variables separately for females and males. Females perform better than

[9] The data available for this project do not include education data for the fall 2010. Thus, we cannot analyse the NEET-outcome for the 2004 cohort.

[10] The mean values of the two variables for labor market attachment differ markedly across high school graduates and high school dropouts. On average, 36.7% of the dropouts are not registered in employment or education on October 15th the year they turn 22 years of age, compared to 9.9% of the graduates. Regarding welfare participation, the corresponding numbers are 6.9 and 0.4%.

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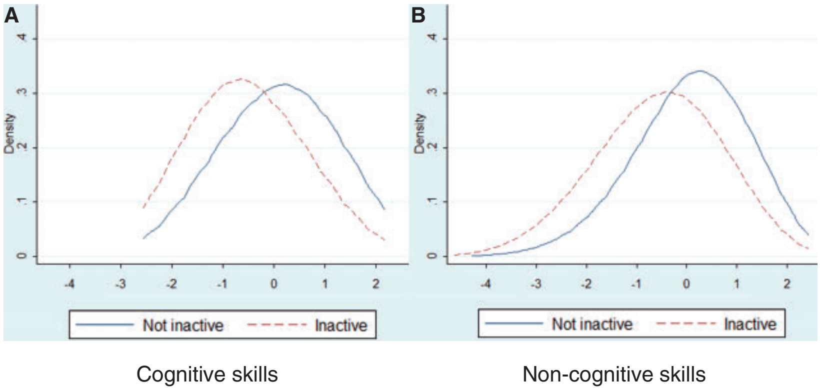

Figure 3 Inactivity and skills.

males on all outcomes. They are more likely to graduate high school and to enroll higher education, and less likely NEET and to receive welfare benefits.

Individual characteristics and family background are well documented as factors affecting individual outcomes. In the empirical analysis we include variables for gender, immigrant status, 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. The dummy variable for 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 the highest education level. 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% of the parents were registered as married, 12.5% were registered as divorced, and 26% had never been married. Descriptive statistics are presented in Appendix Table A1.

3.3 Empirical specification

We use the following regression model to estimate the conditional correlation between outcomes and different skills.

$$Y_{ijc} = \alpha + \beta_1 \text{cog}_{ic} + \beta_2 \text{noncog}_{ic} + X'_{ic}\delta + \gamma_j * \theta_c + \epsilon_{ic} \qquad (1)$$

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The outcome is a binary variable, Y_{ijc}, for student i from compulsory school j in cohort c. We use the following four outcomes; high school graduation, enrolling higher education, NEET, and receiving welfare benefits. The variable 'cog' is defined as the mean grade in Mathematics and Science, and 'noncog' is the mean grade in Physical education, Food and health, Arts and craft, and Music. X_{ic} is a vector of individual characteristics. In addition, the model includes interaction between fixed effects for 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 unobserved 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.

Different kinds of skills interact in student performance and real-life decisions. Thus, our analysis cannot make a strong distinction between cognitive and non-cognitive skills. As in Lindquist and Vestman (2011), it is a positive correlation between the skill variables. Performance in 'non-cognitive' subjects arguably depends on reasoning and other types of cognitive skills. Likewise, the evidence indicates that non-cognitive skills influence performance on tests of cognitive ability, and the acquisition of cognitive skills, see for example Heckman et al. (2006), Lindquist and Vestman (2011), and Segal (2011). Since Mathematics and Science are clearly cognitive subjects, and the grades in these subjects reflect achievement on tests, we are reasonable confident that the grades mainly reflect 'cognitive' skills. Our main concern is that the grades in the 'non-cognitive' subjects capture cognitive skills.

To help interpretation, we will therefore present results from different models that can be regarded as upper and lower bounds of the underlying relationships. Models with only one skill measure included will provide upper bounds of the relationship between outcome and skills, while including both skill measures in the model, as in equation (1), provides lower bounds.[11] As robustness checks, we provide estimates using more flexible model formulations. We estimate non-parametric specifications and models with skills represented by grades in separate subjects rather than average grades in subject categories.

[11] An alternative is to estimate the upper bound of the association with 'cognitive' skills and the lower bound of the association with 'non-cognitive' skills in the same model. This can be achieved by including the residual from an auxiliary regression of non-cognitive skills on cognitive skills in the model instead of the non-cognitive skill measure itself. As this residuals is uncorrelated with the cognitive skills measure by construction, its coefficient will only capture information that is not inherent in the cognitive skills measure. This alternative procedure thus gives exactly the same estimates as those presented in Table 4.

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4 Empirical results

We begin with an analysis of the probability to graduate from high school, with the main emphasis on graduation within 5 years after the end of compulsory education. We also decompose this outcome into graduation on-time and delayed and conduct separate analysis on each component. The last part of the section presents results for the labor market attachment at age 22.

4.1 Educational outcomes

Table 4 presents estimates of the association between skills and the probability to graduate from high school within 5 years after the end of compulsory education (the year the individuals turn 21). The first column presents simple correlations between skills and graduation. To illustrate the strength of the associations, increasing 'cognitive' skills with one standard deviation is associated with 14.3 percentage points higher graduation probability (20% of the sample mean), whereas a similar change in 'non-cognitive' skills is associated with 11.7 percentage points higher graduation probability (17%). These are numerically strong relationships.

Column (2) in Table 4 includes socioeconomic characteristics. Even though several of the socioeconomic characteristics are strongly related to the probability to graduate (see below), the correlations between graduation and the skill measures are only marginally reduced when they are included.

However, since the skill variables are correlated, column (3) shows that the 'cognitive' skills coefficient increases substantially when 'non-cognitive' skills is excluded from the model. In this case, an increase in 'cognitive' skills by one standard deviation is associated with 20.5 percentage points higher graduation probability, which is 55% larger than when both types of skills are included. Similarly, excluding 'cognitive' skills from the model (column (4)) increases the 'non-cognitive' skills coefficient by 87%.[12] As pointed out above, the coefficients in columns (3) and (4) are to be interpreted as upper bounds on the relationship between graduation and the two types of skills.

One concern is that grading standards can vary across schools and may contribute to the estimated correlation between outcomes and skills. 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 larger

[12] In models with cohort by school fixed effects (model specifications similar to the model in column (6) in Table 4), the biases are of similar size (62 and 80% for cognitive and non-cognitive skills, respectively).

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Table 4 The effects of skills on high school graduation within 5 years

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cognitive skills	0.143*	0.132*	0.205*	–	0.129*	0.130*	0.132*
	(0.0019)	(0.0019)	(0.0014)		(0.0018)	(0.0017)	(0.0018)
Non-cognitive skills	0.117*	0.106*	–	0.198*	0.116*	0.117*	0.115*
	(0.0018)	(0.0019)		(0.0014)	(0.0017)	(0.0017)	(0.0018)
Socioeconomic characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
School FE (no. of groups)	0	0	0	0	1,186	0	0
Cohort × school FE (no. of groups)	0	0	0	0	0	3,349	0
Cohort × ward FE (no. of groups)	0	0	0	0	0	0	32,319
R^2	0.285	0.300	0.277	0.264	0.297	0.299	0.289
Observations	154,515	154,515	154,515	154,515	154,515	154,515	154,447

Note: Socioeconomic characteristics are presented in Table A1. Standard errors in parentheses are clustered by compulsory school. * denotes significance at 1% level.

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concern for our measure of 'non-cognitive' skills. If variation in grading practices is merely across schools rather than across classrooms within schools, including school fixed effects would increase the association with 'non-cognitive' skills.

The model in column (5) includes school fixed effects, which increases the 'non-cognitive' skills coefficient by 10%, whereas the 'cognitive' skills coefficient is largely unchanged. On the other hand, if grading practices varies substantially across classrooms within schools, we would expect cohort by school fixed effects to further increase the predictive power of 'non-cognitive' skills since Norwegian teachers usually teaches the same group of students in several years. However, the results when including cohort by school fixed effects (column (6) in Table 4) are basically identical to the previous ones. Finally, in order to investigate if the estimated relationship between skills and outcomes reflects unobserved neighborhood variables, the model in column (7) in Table 4 includes cohort by ward fixed effects. This model specification accounts for detailed neighborhood characteristics since, in each cohort, the average number of students in the ward is only 4.8. Again, the coefficients of the skill variables are similar to those obtained in the simpler specifications.

The full results for the model in column (6) in Table 4 are reported in column (2) in Appendix Table A1. The estimated coefficients of the socioeconomic characteristics are mainly as expected. Conditional on skills, students with married and working parents with some post-compulsory education have higher probability to graduate. There is also a positive relationship between graduation and income 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 must be interpreted as a catch-up effect since those born late appears to have lower school achievement at younger ages (Bedard and Dhuey 2006).[13] 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 relationship is critically dependent on the inclusion of parental characteristics in the model.

The relationship between graduation and skills may be nonlinear. To explore this issue, Figure 4 presents estimated coefficients from a model where the continuous skill variables are replaced by dummy variables for intervals of these variables. Otherwise the model is identical to the model in column (6) in Table 4. The figure presents skill estimates relative to students with normalized skills equal to zero (mean skills).[14] For both skill

[13] This is the case also for both our measures of skills in the present article.

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

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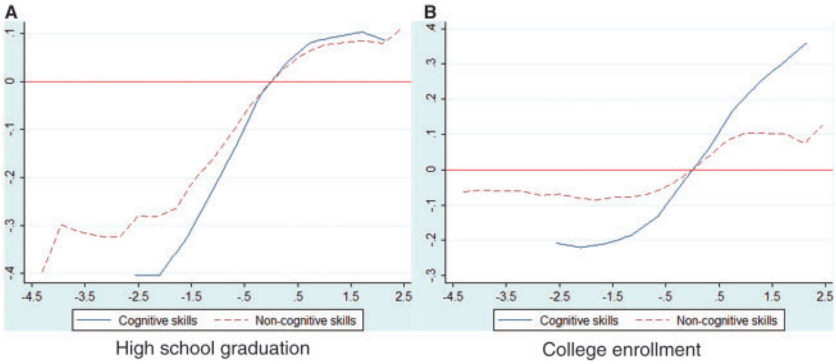

Figure 4 Non-parametric effects of skills on education outcomes.

variables, the estimated coefficients are small in the 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.

One concern is that the 'non-cognitive' skill measure contains more information in the lower end of the distribution than the 'cognitive' skill measure. The combination of this fact and the use of standardized measures may to some extent explain the relatively large predictive power of 'non-cognitive' skills on graduation. However, sensitivity analyses suggest that this is not the case. If we replace the standardized variables with the average grades, the estimated relationships in terms of standard deviations are identical to the results reported in Table 4. In addition, if we disregard the detailed information in the left tail of 'non-cognitive' skills, we also get identical results.[15]

Another issue is that the classification of skills into two categories implies that we do not utilize all the information available in the transcript of records at the end of compulsory education. Table 5 presents estimates using more flexible models and evaluates to what extent grades in individual subjects matter for high school graduation. The first two columns present results for models allowing for independent relationships for

[15] We disregard the detailed information in the left tail of the 'non-cognitive' skills (noncog) distribution in two ways; (i) excluding the 1,743 observations with noncog below the minimum value of 'cognitive' (cog) skills (which is equal to –2.56); and (ii) replacing all values of noncog for these observations with the lowest value of cog. In addition, the results are also robust to excluding all outliers defined as values of cog or noncog larger than two in absolute value (10,652 observations). In this case, the association with cog and noncog in the model formulation with cohort by school fixed effects (column (6) in Table 4) are 0.136 and 0.114, respectively, which are changes of $<5\%$ compared to Table 4.

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each of the subjects used to calculate our measures of skills above. Standardized values are used for all grades.

In the model without fixed effects (column (1)), the association with Science (7.5 percentage points) is slightly larger than the association with 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 unit, holding the grade in Science constant, only increases our measure of 'cognitive' skills by 0.5. Thus, the sum of the coefficients of Mathematics and Science in Table 5 is close to the 'cognitive' skills coefficient in Table 4. For each of the 'non-cognitive' subjects, the coefficient is smaller than for the 'cognitive' subjects. Since the coefficients are very precisely estimated, we formally reject the hypothesis of equal effects of all four 'non-cognitive' subjects even though they are not very different in numerical terms. Column (2) in Table 5 shows that taking unobserved heterogeneity across schools and cohorts into account increases the coefficients of all subjects except for Mathematics, which is the only of these subjects with an external written exit examination.

The models in columns (3) and (4) in Table 5 include the grades in all subjects in the transcript of record. In addition to the subjects above, that includes three different grades in Norwegian language, two grades in English language, Religious and ethical education, and Social studies (including history).[16] The coefficients of both oral and written English are insignificant, while the coefficients of the three grades in Norwegian language are small. Language skills do not seem to be important for the probability to graduate high school, conditional on the other grades. The grades in Religious and ethical education and Social studies, however, turn out to be strongly related to the probability to graduate, and in particular the performance in Social studies. In our view, it is, however, hard to classify the skills inherent in these subjects compared to the other subjects. To simplify the exposition of the article, we thus restrict the succeeding analyses to 'cognitive' and 'non-cognitive' skills as defined above. Notice that by this approach the impact of skills inherent in the other subjects is partly taken into account by the positive correlation between the grades in the different subjects. That is visualized in Table 5, by the fact that the coefficients of the 'cognitive' and 'non-cognitive' subjects decline by 18–47% when the grades in the other subjects are included.

The high school graduation outcome used so far may be decomposed into graduating on-time and graduating delayed, but within 5 years after

[16] Since information is missing for some individuals for some of these additional subjects, the number of observations declines by 1.3% compared to the former models.

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

	(1)	(2)	(3)	(4)
Mathematics	0.065*	0.059*	0.046*	0.039*
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Science	0.076*	0.082*	0.041*	0.045*
	(0.0021)	(0.0020)	(0.0023)	(0.0022)
Physical education	0.043*	0.044*	0.035*	0.037*
	(0.0015)	(0.0014)	(0.0015)	(0.0014)
Food and health (home economics)	0.026*	0.032*	0.019*	0.024*
	(0.0017)	(0.0015)	(0.0017)	(0.0015)
Arts and crafts	0.034*	0.038*	0.027*	0.031*
	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Music	0.032*	0.035*	0.017*	0.019*
	(0.0018)	(0.0016)	(0.0018)	(0.0017)
Norwegian, written	–	–	0.006*	0.009*
			(0.0021)	(0.0020)
Second Norwegian language, written	–	–	0.001	-0.002
			(0.0019)	(0.0018)
Norwegian, oral	–	–	0.016*	0.017*
			(0.0020)	(0.0020)
English, written	–	–	–0.000	–0.001
			(0.0020)	(0.0020)
English, oral	–	–	–0.003	–0.003
			(0.0021)	(0.0020)
Religious and ethical education	–	–	0.031*	0.032*
			(0.0023)	(0.0022)
Social studies	–	–	0.044*	0.044*
			(0.0021)	(0.0020)
Socioeconomic characteristics	Yes	Yes	Yes	Yes
Cohort $\times$ school FE (no. of groups)	0	3,349	0	3,340
R^2	0.300	0.299	0.305	0.304
Observations	154,515	154,515	152,468	152,468

Note: The same socioeconomic characteristics as in the models in Table 4 are included. 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 includes an indicator for missing value. Standard errors in parentheses are clustered at the school level. * denotes significance at 1% level.

compulsory education. Most students graduate on-time (3 or 4 years after compulsory education, depending on study track). Panel B in Table 6 presents results for this outcome. Compared to the results for graduation within 5 years (replicated in panel A in the table), 'cognitive' skills seem slightly more important and 'non-cognitive' skills slightly less important,

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Table 6 The effect of skills on educational outcomes

Sample	(1) All	(2) All	(3) Females	(4) 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
D. College enrollment				
Cognitive skills	0.173*	0.178*	0.175*	0.179*
	(0.0017)	(0.0017)	(0.0027)	(0.0023)
Non-cognitive skills	0.048*	0.052*	0.079*	0.030*
	(0.0017)	(0.0017)	(0.0028)	(0.0022)
Observations	154,515	154,515	75,778	78,737
Socioeconomic characteristics	Yes	Yes	Yes	Yes
Cohort × school FE	No	Yes	Yes	Yes

Note: The same socioeconomic characteristics as in the models in Table 4 are included. Standard errors in parentheses are clustered at the school level. * denotes significance at 1% level.

but the differences are small. Panel C in Table 6 shows results for the probability to graduate delayed. We restrict the sample to individuals not graduating on-time. Also in this case, both skill measures are strongly associated with increased probability to graduate. Increasing 'cognitive' skills by one standard deviation is associated with an increase in the probability to graduate on-time and delayed by 16 and 11 percentage points, respectively. However, since the share of students graduating on-time is much higher than the share graduating delayed, the associations between skills and graduating delayed is largest in relative terms (27 and 36%, respectively, evaluated at sample means). For both graduation on-time

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and graduation delayed, the change in the estimated associations when excluding one of the skill variables from the model is similar to the models above.[17]

The final education outcome is enrollment in higher education 5 years after the end of compulsory education. Panel D in Table 6 shows that the association between enrollment and 'cognitive' skills is almost four times larger than the association between enrollment and 'non-cognitive' skills. Although the predictive power of the latter skill variable is relatively small, it is significant at 1% level. Although this result is as expected, the effects are clearly nonlinear as shown in Panel B in Figure 4. There is no association between college enrollment and 'cognitive' skills for the 15% of the individuals with lowest skills (weaker than one standard deviation below mean). The predictive power of 'non-cognitive' skills is concentrated to individuals with skills in the range ± 1 standard deviation from mean. We note that this group of students is likely to be on the margin of enrolling into higher education or not as the share of the cohort enrolling is 37%.

An interesting issue is to what extent the estimated relationships vary by gender. The last two columns in Table 6 estimate separate models for females and males. Although the gender differences are relatively small, it turns out that the associations with 'cognitive' skills are stronger for males than for females for all outcomes. The opposite is the case for 'non-cognitive' skills, except for delayed graduation.[18] Although these patterns are interesting, our data do not enable us to further explore why the relationship between skills and these outcomes differ between males and females.

4.2 Labor market outcomes

Table 7 presents the models for the probability of receiving welfare benefits and inactivity (NEET). Regarding the probability of receiving welfare benefits in Panel A, the 'non-cognitive' skill coefficient is about four times larger than the 'cognitive' skill coefficient. Thus, the relative importance of the different skills for this outcome is directly opposite to the results for enrollment in higher education. This is reassuring and consistent with the

[17] For the models without school fixed effects (column (1) in Table 6), the change in the coefficient of 'cognitive' skills when excluding 'non-cognitive' skills from the model is 43% for both graduation on-time and graduation delayed. For the model including cohort by school fixed effects (column (2)), the corresponding change is 46 and 48%, respectively.

[18] The standard deviations of the skill variables are slightly smaller for females than for males. For females (males), the standard deviations of 'cognitive' skills and 'non-cognitive' skills are 0.97 (1.01) and 0.93 (1.01), respectively. Thus, in terms of standard deviations, the associations in percentage points are qualitatively the same as in Table 6. The differences across gender in percent of average values of the dependent variables are even larger because males graduate high school to a smaller degree than females.

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Table 7 The effect of skills on lack of labor market attachment at age 22

Sample	(1) All	(2) All	(3) All	(4) All	(5) Females	(6) Males
A. On welfare						
Cognitive skills	–0.0044*	–0.0168*	–	–0.0038*	–0.0035*	–0.0039*
	(0.0004)	(0.0004)		(0.0004)	(0.0006)	(0.0006)
Non-cognitive skills	–0.0180*	–	–0.0211*	–0.0196*	–0.0210*	–0.0190*
	(0.0006)		(0.0005)	(0.0007)	(0.0010)	(0.0009)
Observations	154,515	154,515	154,515	154,515	75,778	78,737
B. Inactive (2002–2003 cohorts)						
Cognitive skills	–0.0418*	–0.0751*	–	–0.0399*	–0.0423*	–0.0368*
	(0.0019)	(0.0014)		(0.0019)	(0.0028)	(0.0026)
Non-cognitive skills	–0.0484*	–	–0.0772*	–0.0549*	–0.0602*	–0.0520*
	(0.0020)		(0.0015)	(0.0021)	(0.0031)	(0.0029)
Observations	99,940	99,940	99,940	99,940	49,003	50,937
Socioeconomic characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × school FE	No	No	No	Yes	Yes	Yes

Note: The same socioeconomic characteristics as in the models in Table 4 are included. Standard errors in parentheses are clustered at the school level. * denotes significance at 1% level.

view that our measures based on grades in different subjects to some extent captures the effects of cognitive and non-cognitive skills traditionally used in the literature. In columns (2) and (3) we include the skill measures separately to indicate the upper bounds on the relationships. Whereas the increase in the 'non-cognitive' skills coefficient is relatively modest from 0.018 to 0.021 (17%), the 'cognitive' skills coefficient more than triples. However, we notice that the lower bound on the estimated coefficient of non-cognitive skills (0.018) is above the upper bound on the cognitive skill coefficient (0.017). This result is remarkably similar to the relative importance of cognitive and non-cognitive skills for the probability to receive unemployment support, disability insurance and social welfare payments found in the Swedish data in Lindquist and Vestman (2011).

The results in the fixed effects specification (column (4)) imply that, on average, increasing 'non-cognitive' skills by one standard deviation is associated with a decline in the probability of being on welfare by 1.96 percentage points, i.e., 102% of the average rate of welfare participation. This is indeed a strong association, and it is nonlinear as shown in Panel A in Figure 5. The small association when 'non-cognitive' skills exceed –0.5 is likely to reflect the fact that very few individuals with high skills receive welfare benefits. If we disregard the detailed information in the left tail of this skill variable, the estimated coefficients change slightly, but the

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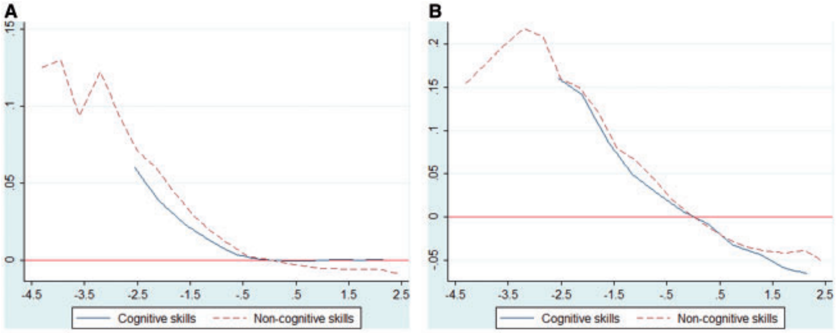

Figure 5 Non-parametric effects of skills on labor market attachment.

qualitative results remain. Using the same robustness checks as above, the largest change is for the model where we exclude all observations with skill measures larger than two in absolute value. In this case the association with 'cognitive skills' increases from –0.0038 to –0.0047 and for 'non-cognitive' skills it decreases from –0.0196 to –0.0133.[19]

The outcome variable in Panel B in Table 7 is the probability to be inactive (NEET), but the relative importance of 'non-cognitive' and 'cognitive' skills is qualitatively similar to the probability of receiving welfare. However, the numerical differences across the skill variables are smaller. In the fixed effects model in column (4), the change in inactivity (NEET) associated with a one standard deviation increase in 'non-cognitive' and 'cognitive' skills are –5.5 and –4.0 percentage points (34 and 24%), respectively. These relationships are close to linear as shown in Panel B in Figure 5.[20]

Columns (2) and (3) present the upper bound correlations between NEET and the two skill measures. The association with 'cognitive' skills increases by 85% when the 'non-cognitive' skill variable is excluded from the model. Similarly, the association with 'non-cognitive' skills increases by 60% when the 'cognitive' skill variable is excluded from the model. Overall, the change in the predictive power of 'cognitive' skills when 'non-

[19] If we replace the standardized variables with the average grades, the associations in terms of standard deviations are identical to the results reported in Table 7. When excluding the 1,743 observations with 'non-cognitive' skills (noncog) below the minimum value of 'cognitive' skills (cog), or replace these values with the minimum value of cog, the estimated coefficient of cog increases by about 20% and the coefficient of noncog decreases by about 15%, which imply that the association between the outcome and noncog is about 3.5 times larger than that of cog.

[20] The estimated coefficients are insensitive to the differences in the distribution of the skill variables. Using the same approaches as above, the cog coefficient varies from –0.0404 to –0.0413 and the noncog coefficient varies from –0.0474 to –0.0551.

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cognitive' skills is excluded from the model is larger for the outcomes in Table 7 than for the outcomes in Table 6. This is related to the finding that the latter skill variable is of much more importance for labor market attachment than the former.

The last two columns in Table 7 present separate models for males and females. The results are qualitatively similar to the gender differences for the educational outcomes. In general, the gender differences are relatively small, but the estimated coefficients of 'cognitive' skills are higher for males than for females, whereas the coefficients of 'non-cognitive' skills are higher for females than for males.

Overall, both skill types seem to matter for labor market attachment for young adults. Of special interest is the finding that 'non-cognitive' skills are more important than 'cognitive' skills which is similar to the Swedish evidence for males in Lindquist and Vestman (2011). It is interesting to note that we reach a similar conclusion using clearly different measures of skills compared to their study. In addition, we find a similar pattern for females as for males.

5 Concluding remarks

This article investigates the association between different types of skills and performance of young adults. We use detailed grade transcripts from compulsory education in Norway at age 16, 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 the two skill types are of roughly equal importance for the probability to graduate from high school, and that the effect sizes depend on whether the measures of both classes of skill are included in the model or not. 'Cognitive' skills are of much more importance than 'non-cognitive' skills for college enrollment, while the opposite is the case for labor market attachment. Interestingly, this pattern is in accordance with results from other studies using measures of cognitive and non-cognitive skills very different from ours. It seems like cognitive skills are most important for educational outcomes, whereas non-cognitive skills are most important for poor outcomes in the labor market. In addition, there is some weak evidence that cognitive skills are relatively more important for males than for females, whereas non-cognitive skills in general is relatively more important for females.

Although we document that different types of skills at age 16 are strongly related to the performance of young adults, the present article is less informative on underlying mechanisms, a feature it has in common with other papers in literature. It is challenging to provide compelling

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evidence on mechanisms in non-causal analyses. The strong associations between skills and the probability of graduating high school can in principle be related to selective admission and different graduation standards. However, this seems less likely to be the case in Norway where the distribution of school resources is highly compensatory. Schools and study tracks recruiting weak students typically receive more resources. The redistribution policy argument also suggests that schools and tracks with weak students, if anything, have lower graduation standards than more selective ones. However it is interesting in future research to provide more evidence of this issue.

Non-activity at age 22 might be related to positive selection in to non-compulsory education rather than a negative selection directly into inactivity. However, our finding that different kinds of skills are predictive for starting college and to be registered as inactive is less supportive of such selection mechanisms and rather indicate that it is skills per see that drive the relationship.

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Table A1 Descriptive statistics and full model results

	(1) Mean values	(2) Graduation	(3) On welfare	(4) NEET
Cognitive skills	0.00 [1.00]	0.130*	–0.0038*	–0.0399*
		(0.00171)	(0.0004)	(0.0019)
Non-cognitive skills	0.00 [1.00]	0.117*	–0.0196*	–0.0549*
		(0.00170)	(0.0007)	(0.0021)
Female	0.49	0.00587*	0.0080*	0.0151*
		(0.00226)	(0.0006)	(0.0027)
First generation immigrant	0.03	0.0454*	–0.0133*	–0.0029
		(0.00723)	(0.0025)	(0.0091)
Second generation immigrant	0.02	0.0515*	–0.0182*	–0.0130
		(0.00825)	(0.0019)	(0.0100)
Parents' highest educational level is high school education	0.47	0.0437*	–0.0117*	–0.0230*
		(0.00358)	(0.0013)	(0.0044)
Parents' highest educational level is bachelor degree	0.29	0.0577*	–0.0095*	–0.0219*
		(0.00385)	(0.0013)	(0.0047)
Parents' highest educational level is master or PhD	0.1	0.0418*	–0.0059*	–0.0173*
		(0.00452)	(0.0013)	(0.0055)
Benefits due to disease before the age of 18	0.02	0.0108	0.0005	0.0142
		(0.00835)	(0.0030)	(0.0112)
Benefits due to disabilities before the age of 18	0.02	–0.0557*	0.0127*	0.0661*
		(0.00774)	(0.0029)	(0.0105)
One parent employed	0.24	0.0399*	–0.0258*	–0.0295*
		(0.00546)	(0.0026)	(0.0071)
Both parents employed	0.71	0.0706*	–0.0337*	–0.0582*

(continued)

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Table A1 Continued

	(1) Mean values	(2) Graduation	(3) On welfare	(4) NEET
		(0.00555)	(0.0025)	(0.0072)
Parental income in 100,000 NOK	6.05 [3.98]	0.00120*	–0.0004*	–0.0014*
		(0.000328)	(0.0001)	(0.0004)
Parental income in 100 NOK squared	52.5 [995.2]	–0.0023*	0.0000*	0.0000
		(7.72e-07)	(0.0000)	(0.0000)
Married parents	0.61	0.0511*	–0.0113*	–0.0196*
		(0.00262)	(0.0008)	(0.0031)
Divorced parents	0.12	0.00619	–0.0035*	–0.0029
		(0.00349)	(0.0012)	(0.0045)
Mobility	0.11	–0.0439*	0.0143*	0.0264*
		(0.00344)	(0.0013)	(0.0040)
Mobility unknown	0.02	–0.00931	–0.0008	0.0280*
		(0.00879)	(0.0028)	(0.0108)
Born second quartile	0.27	0.00912*	–0.0007	–0.0060
		(0.00268)	(0.0007)	(0.0033)
Born third quartile	0.26	0.0228*	–0.0011	–0.0098*
		(0.00274)	(0.0007)	(0.0031)
Born fourth quartile	0.23	0.0297*	–0.0028*	–0.0098*
		(0.00289)	(0.0008)	(0.0033)
Observations	154,515	154,515	154,515	99,940
R^2	–	0.299	0.070	0.073
Cohort × school FE (no. of groups)	–	3,349	3,349	2,230

Note: Standard deviations in brackets. Standard errors in parentheses are clustered by compulsory school. * denotes significance at 1% level.

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