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Performance of young adults: The importance of different skills

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Performance of Young Adults: The Importance of Different Skills

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Abstract

This paper uses teacher assessments at age 16 in Norwegian comprehensive schools to measure different types of skills. While we follow the literature and interpret test scores 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 fairly strong and equal effects of the two types of skills on high school graduation probabilities. However, we find that “non-cognitive” skills has a much larger impact than “cognitive” skills on the probability to receive welfare benefits or being inactive (NEET) at age 22, while the findings are the opposite for the probability of college enrollment.

JEL-Code: I210, J240.

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

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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). The evidence indicates that non-cognitive skills explain as much of the variation in earnings and employment prospects as cognitive skills. While cognitive skills traditionally are measured by some test score, measures of non-cognitive skills are usually based on self-reported survey data. Heckman et al. (2006) and Carneiro et al. (2007) estimate effects of indicators for loss of control and self-esteem, while a popular concept in the psychology literature is the five-factor model shaping human personality (Digman, 1990, Mueller and Plug, 2006, Borghans et al. 2008).

The reliance in the literature 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. The present paper has a different approach. Instead of relying on survey information, we use detailed information from transcript of records at the end of compulsory education at age 16 in Norway. Thus, we estimate the effect of the skills that are regarded as important by the school system and evaluated objectively by teachers. We distinguish between skills reflected in achievement in Mathematics and Science and skills reflected in performance in "behavioral and practical" subjects such as Arts and crafts and Physical education. By this approach, the observed skills cannot be directly compared to cognitive and non-cognitive skills as measured in the existing literature. For simplicity, however, we denote the former for "cognitive skills", in line with several other studies, and the latter for "non-cognitive skills". Teacher assessed grades in the latter subjects arguably reflect 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 and motivation rather than just particular performance in sports.

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 data for the cohorts leaving compulsory education in 2002–2004. We find that performance of young adults is strongly associated with both types of skills. Further, the estimated effect of one type of skill is biased by exclusion of the other type.

The empirical models include a rich set of individual characteristics, and the results are robust to the inclusion of different sets of school and neighborhood fixed effects. Although the results seem robust, we do not claim that estimated effects can 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.

The paper 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 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 achievement measures are 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 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, 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.

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. 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 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 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) exploits 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 while 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 US and studies the impact of premarket teacher reported student misbehavior in eight grade (tardiness, absence, disruptiveness etc.) on 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) only consider the impact of cognitive and non-cognitive skills on outcomes for males. Our data include the total student population, and allow us to investigate whether the return to different skill types differs 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 ten compulsory years. Students are normally enrolled the year they turn six years, and there is no possibility to fail a class. All students finish compulsory education 10 years after enrollment.

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, 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 three years, while the vocational study tracks normally consist of two years in school plus two 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 five year as the measure of the graduation rate in official statistics. Therefore, we use a five-year window in the empirical study of high school graduation below.

About 95 percent 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 enrolment rate, only around 70 percent of each cohort graduate within five years. A large fraction of the 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.¹ 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

¹ Few students enroll in private schools. About two and five percent of a cohort enroll in private compulsory schools and high schools, respectively.

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.² 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 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. Recognizing that the same types of skills might improve the grades in several different subjects, isolating the impact of one type of skill, say, cognitive skills, requires that the model condition on other types of skills. Analyses that only include one skill measure might overestimate the importance of this type of skill.³

² 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.

³ 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

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 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. 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 mean.⁴ 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.⁵

Table 3 gives a description of educational and labor market outcomes. About 57 percent graduate within expected time, while additionally about 14 percent 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 five years is clearly to the right of the distribution for dropouts. Panel B shows a similar picture for “non-cognitive” skills.⁶

We measure enrollment in higher education in the fall five 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 three years, the individuals might

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.

⁴ 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.

⁵ The skill variables are discrete, but the presentation of the distributions in the lower part of Figure 1 and Figures 2-3 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.

⁶ 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.

do military services or other activities 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 percent.

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).⁷ Table 3 shows that 16.3 percent 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 percent are on welfare in a random month the year they turn 22. During this year, about five percent of the sample receive welfare benefits at least one month.⁸

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

⁷ The data available for this project do not include education data for the fall 2010. Thus, we cannot analyze the NEET-outcome for the 2004 cohort.

⁸ 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 percent of the dropouts are not registered in employment or education at October 15 the year they turn 22 years of age, compared to 9.9 percent of the graduates. Regarding welfare participation, the corresponding numbers are 6.9 and 0.4 percent.

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 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 A1.

3.3. Empirical specification

We use the regression model in equation (1) to estimate the impact of different skills on the following outcomes; high school graduation, enrolling higher education, NEET, and welfare participation. The outcome is a binary variable, Y_{ijc} , for student i from compulsory school j in cohort c . 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.

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

As robustness checks, we provide estimates using more flexible model formulations. We estimate non-parametric specifications and models with skills represented by grades in separate subjects rather than average grades in subject categories.

4. Empirical results

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. 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 the estimated effects of 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 of the 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 4 includes socioeconomic characteristics. Even though several of the socioeconomic characteristics are strongly related to the probability to graduate (see below), the effects of the skill measures are only marginally reduced when they are included.

However, the skill variables are correlated. Column (3) shows that the effect of “cognitive” skills increases to 20.5 percentage points when “non-cognitive” skills is excluded from the model, an increase of 55 percent. This result clearly indicates that estimates of cognitive skills as measured by achievement in mathematics and science are biased in models not taking other kinds of skills into account. Similarly, excluding “cognitive” skills from the model as in column (4) increases the effect of “non-cognitive” skills by 87 percent.⁹

One concern is that grading standards can vary across schools and introduce biased estimates of the coefficients. In this case we would expect the coefficients in column (2) in Table 4 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 larger concern for our measure of “non-cognitive” skills. If variation in grading practices is merely across schools rather than across classrooms within schools, school fixed effects will reduce the potential bias. The model in column (5) includes school fixed

⁹ 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 percent for cognitive and non-cognitive skills, respectively).

effects, which increases the effect of “non-cognitive” skills, but does not change the effect of “cognitive” skills. 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 estimated effects 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 control for unobserved neighborhood effects, the model in column (7) in Table 4 includes cohort specific 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 effects 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 effects of the socioeconomic characteristics are mainly as expected. Conditional on skills, individuals with married and working parents with some post-compulsory education have a higher 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 appears to have lower school achievement at younger ages (Bedard, 2006).¹⁰ 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 the inclusion of parental characteristics in the model.

The effects of skills may be non-linear. To explore this issue, Figure 4 presents estimated skill effects from a model where the continuous skill variables are replaced by dummy variables for the observed values of these discrete variables. Otherwise the model is identical to the model in column (6) in Table 4. The figure presents estimated skill effects relative to students with normalized skills equal to zero (mean skills).¹¹ For both skill variables, 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.

¹⁰ This is the case also for both our measures of skills in the present paper.

¹¹ 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.

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 slightly larger effect of “non-cognitive” than “cognitive” skills on the graduation. However, sensitivity analyses suggest that this is not the case. If we replace the standardized variables with the average grades, the effects 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.¹²

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 presents results for models allowing for independent effects of 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 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 5 is close to the effect of “cognitive” skills in Table 4. 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 5 shows that taking unobserved heterogeneity across schools and cohorts into account increases

¹² 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 effects of *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 less than five percent compared to Table 4.

the effects of all grades except the grade in 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).¹³ The effects of both oral and written English are insignificant, and the effects 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, have significant effects, and in particular the performance in Social studies has predictive power on the probability to graduate. 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 paper, 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 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 effects of the “cognitive” and “non-cognitive” subjects decline by 18-47 percent when the grades in the other subjects are included.

The graduation outcome used so far may be decomposed into graduating on time and graduating delayed, but within five years after compulsory education. Most students graduate on-time (three or four 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 five years (replicated in panel A 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 6 shows results for the probability to graduate delayed. In this case we restrict the sample to individuals not graduating on-time. Both skill measures 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 students graduating on time is much higher than the share graduating delayed, the effect on graduating delayed is largest in relative terms (the

¹³ Since information is missing for some individuals for some of these additional subjects, the number of observations declines by 1.3 percent compared to the former models.

effects are 27 and 36 percent, respectively, evaluated at sample means). For both graduation on-time and graduation delayed, the bias by excluding one skill variable from the model is similar to the models above.¹⁴

The final education outcome is enrollment in higher education five years after the end of compulsory education. Panel D in Table 6 shows that the effect of “cognitive” skills is almost four times larger than the effect of “non-cognitive” skills for college enrollment. Although the effect of the latter skill variable is relatively small, it is significant at one percent level. While this result is as expected, the effects are clearly non-linear as shown in Panel B in Figure 4. There is no effect of “cognitive” skills for the 15 percent of the individuals with lowest skills (weaker than one standard deviation below mean), while the effect 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 percent.

An interesting issue is to what extent the skill effects on the education outcomes vary by gender. The last two columns in Table 6 estimate separate effects for females and males. Although the gender differences are relatively small, it turns out that the effect of “cognitive” skills is higher for males than for females for all outcomes. The opposite is the case for “non-cognitive” skills, except for delayed graduation. While these patterns are interesting, our data does not enable us to further explore why the skill effects on these outcomes differ between males and females.

4.2. Labor market outcomes

Table 7 presents the estimated effects of skills on the probability of receiving welfare benefits and inactivity (NEET). Regarding the probability of being on welfare, the effect of “non-cognitive” skills is 4-5 times larger than the effect of “cognitive” skills, in contrast to the results for enrollment in higher education. The results in the fixed effects specification imply that, on average, increasing “non-cognitive” skills by one standard deviation decreases the probability of being on welfare by 1.96 percentage points, i.e., 102 percent of the average rate of welfare participation. This is indeed a

¹⁴ For the models without school fixed effect (column 1 in Table 6), 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 cohort by school fixed effects (column 2), the bias is 46 and 48 percent, respectively.

large effect, and it is nonlinear as shown in Panel A in Figure 5. The small effect 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 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 effect of “cognitive skills” increases from -0.0038 to -0.0047 and the effect of “non-cognitive” skills decreases from -0.0196 to -0.0133.¹⁵

Panel B in Table 7 shows that the effect of “non-cognitive” skills is larger than the effect of “cognitive” skills also for the probability of being inactive (NEET). The difference in effect size is, however, smaller than for being on welfare. In the fixed effects model, the effects of increasing skills by one standard deviation are -5.5 and -4.0 percentage points (34 and 24 percent), respectively. These relationships are close to linear as shown in Panel B in Figure 5.¹⁶

The change in the estimated effect of “cognitive” skills of excluding the variable for “non-cognitive” skills from the model is larger for the outcomes in Table 7 than for high school graduation (not reported in the table). This must be related to the finding that the latter skill variable is much more important for labor market attachment than the former.¹⁷

The last two columns of Table 7 presents separate models for males and females. The results are qualitatively similar to the gender differences for the educational

¹⁵ If we replace the standardized variables with the average grades, the effects 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 effect of *cog* increases by about 20 percent and the effect of *noncog* decreases by about 15 percent, which imply that the effect of *noncog* is about 3.5 times larger than the effect of *cog*.

¹⁶ The estimated coefficients are insensitive to the differences in the distribution of the skill variables. Using the same approaches as above, the effect of *cog* varies from -0.0404 to -0.0413 and the effect of *noncog* varies from -0.0474 to -0.0551.

¹⁷ The change in the estimated effect of “cognitive” skills of excluding “non-cognitive” skills from the model is in the order of 350 and 100 percent for being on welfare and NEET, respectively. On the other hand, the change in the estimated effect of “non-cognitive” skills of excluding “cognitive” skills from the model is much smaller, about 15 and 50 percent for being on welfare and NEET, respectively.

outcomes. In general, the gender differences are relatively small, but the effect of “cognitive” skills is higher for males than for females and the effect of “non-cognitive” skills is higher for females than for males.

Overall, both classes of skill seem to be important for labor market attachment for young adults. The finding that “non-cognitive” skills are more important than “cognitive” skills 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 paper investigates the impact of different types of skills on educational outcomes and labor attachment for 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 both classes of skill 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, while non-cognitive skills are most important for the probability of exclusion. In addition, the evidence in this paper indicates that the impact of cognitive skills in general is larger for males than for females, while the impact of non-cognitive skills in general is larger for females than for males.

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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) |

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 calculate our measures of cognitive and non-cognitive skills.

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

| | 2002 | 2003 | 2004 | All | Females | Males |
|--|--------|--------|--------|---------|---------|--------|
| Graduating within 5 years, percent | 70.8 | 70.6 | 71.2 | 70.8 | 75.6 | 66.3 |
| On-time graduation, percent | 57.3 | 56.8 | 57.0 | 57.1 | 64.5 | 49.9 |
| Graduating delayed but within 5 years, percent | 13.4 | 13.7 | 14.2 | 13.8 | 11.0 | 16.4 |
| Enrolled in higher education at age 21, percent | 36.5 | 36.6 | 37.8 | 37.0 | 45.8 | 28.5 |
| NEET October 15 th at age 22, percent | 15.9 | 16.7 | - | 16.3 | 15.1 | 17.4 |
| Share of month on welfare at age 22, percent | 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 |

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

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|-----------------------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| Cognitive skills | 0.143* (0.0019) | 0.132* (0.0019) | 0.205* (0.0014) | - | 0.129* (0.0018) | 0.130* (0.0017) | 0.132* (0.0018) |
| Non-cognitive skills | 0.117* (0.0018) | 0.106* (0.0019) | - | 0.198* (0.0014) | 0.116* (0.0017) | 0.117* (0.0017) | 0.115* (0.0018) |
| Socioeconomic characteristics | No | Yes | Yes | Yes | Yes | Yes | Yes |
| School FE (no of groups) | 0 | 0 | 0 | 0 | 1,186 | - | - |
| Cohort x school FE (no of groups) | 0 | 0 | 0 | 0 | 0 | 3,349 | - |
| Cohort x ward FE (no of groups) | 0 | 0 | 0 | 0 | 0 | 0 | 32,319 |
| R-squared | 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. Standard errors in parentheses are clustered by compulsory school, * denotes significance at one percent level.

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 x school FE (no of groups) | 0 | 3,349 | 0 | 3340 |
| R-squared | 0.300 | 0.299 | 0.305 | 0.304 |
| Observations | 154,515 | 154,515 | 152,468 | 152,468 |

Note. Same model socioeconomic characteristics as in the models in Table 4. 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. Standard errors in parentheses are clustered at the school level. * denotes significance at one percent level.

Table 6. The effect of skills on educational outcomes

| Sample | (1) | (2) | (3) | (4) |
|--|---------------------|---------------------|---------------------|---------------------|
| | All | All | Females | Males |
| A. Graduation within 5 years | | | | |
| Cognitive skills | 0.132* (0.00192) | 0.130* (0.00171) | 0.114* (0.0024) | 0.144* (0.0023) |
| Non-cognitive skills | 0.106* (0.00185) | 0.117* (0.00170) | 0.128* (0.0025) | 0.110* (0.0023) |
| Observations | 154,515 | 154,515 | 75,778 | 78,737 |
| B. On-time graduation | | | | |
| Cognitive skills | 0.156* (0.0019) | 0.157* (0.0018) | 0.145* (0.0026) | 0.165* (0.0024) |
| Non-cognitive skills | 0.097* (0.0020) | 0.106* (0.0018) | 0.125* (0.0027) | 0.094* (0.0024) |
| Observations | 154,515 | 154,515 | 75,778 | 78,737 |
| C. Delayed graduation, but within 5 years | | | | |
| Cognitive skills | 0.110* (0.0030) | 0.112* (0.0029) | 0.099* (0.0050) | 0.121* (0.0037) |
| Non-cognitive skills | 0.064* (0.0024) | 0.073* (0.0025) | 0.070* (0.0042) | 0.075* (0.0032) |
| Observations | 66,348 | 66,348 | 26,877 | 39,471 |
| D. College enrollment | | | | |
| Cognitive skills | 0.173** (0.0017) | 0.178** (0.0017) | 0.175** (0.0027) | 0.179** (0.0023) |
| Non-cognitive skills | 0.048** (0.0017) | 0.052** (0.0017) | 0.079** (0.0028) | 0.030** (0.0022) |
| Observations | 154,515 | 154,515 | 75,778 | 78,737 |
| 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 4 are included. Standard errors in parentheses are clustered at the school level, * denotes significance at one percent level.

Table 7. The effect of skills on lack of labor market attachment at age 22, 2002-cohort

| | (1) | (2) | (3) | (4) |
|-------------------------------|----------------------|----------------------|----------------------|----------------------|
| Sample | All | All | Females | Males |
| A. On welfare | | | | |
| Cognitive skills | -0.0044* (0.0004) | -0.0038* (0.0004) | -0.0035* (0.0006) | -0.0039* (0.0006) |
| Non-cognitive skills | -0.0180* (0.0006) | -0.0196* (0.0007) | -0.0210* (0.0010) | -0.0190* (0.0009) |
| Observations | 154,515 | 154,515 | 75,778 | 78,737 |
| B. Inactive | | | | |
| Cognitive skills | -0.0418* (0.0019) | -0.0399* (0.0019) | -0.0423* (0.0028) | -0.0368* (0.0026) |
| Non-cognitive skills | -0.0484* (0.0020) | -0.0549* (0.0021) | -0.0602* (0.0031) | -0.0520* (0.0029) |
| Observations | 99,940 | 99,940 | 49,003 | 50,937 |
| 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 4 are included. Standard errors in parentheses are clustered at the school level, * denotes significance at one percent level.

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

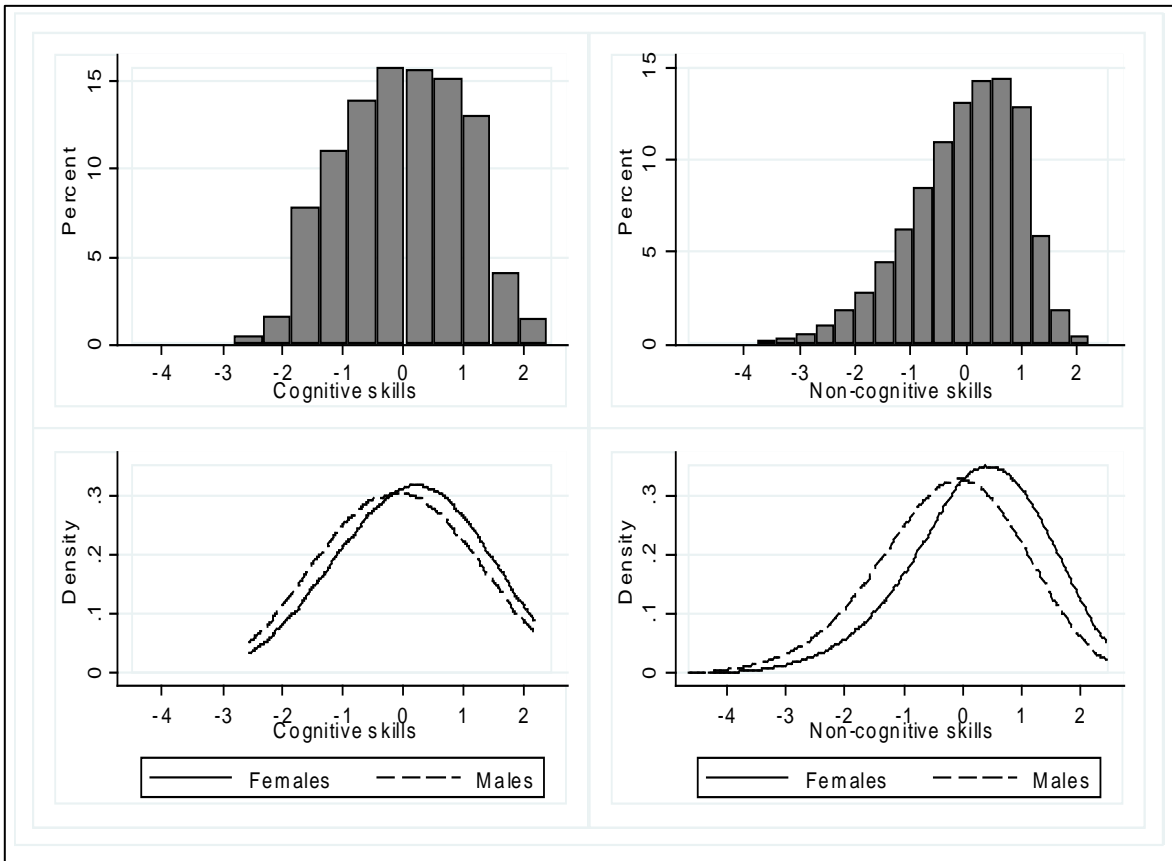
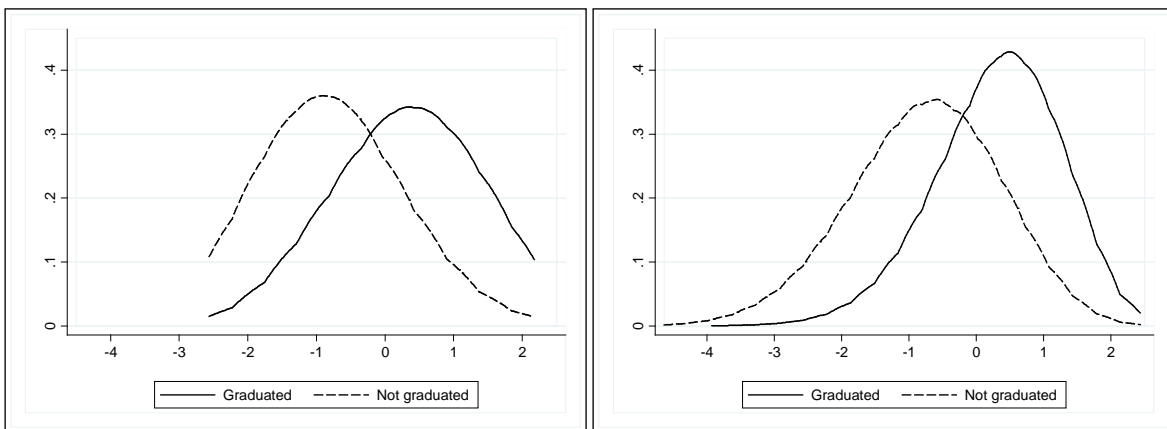


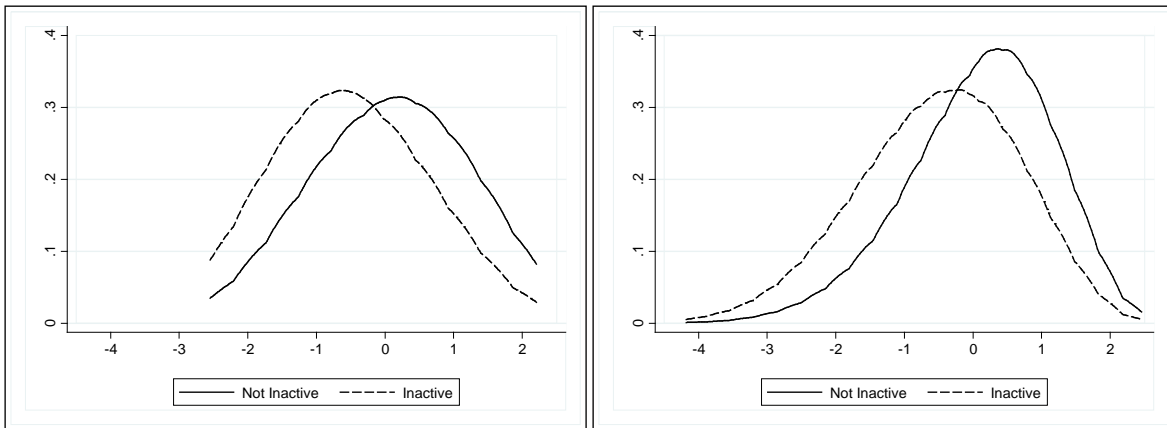
Figure 2. Graduation within five years and skills



Panel A. Cognitive skills

Panel B. Non-cognitive skills

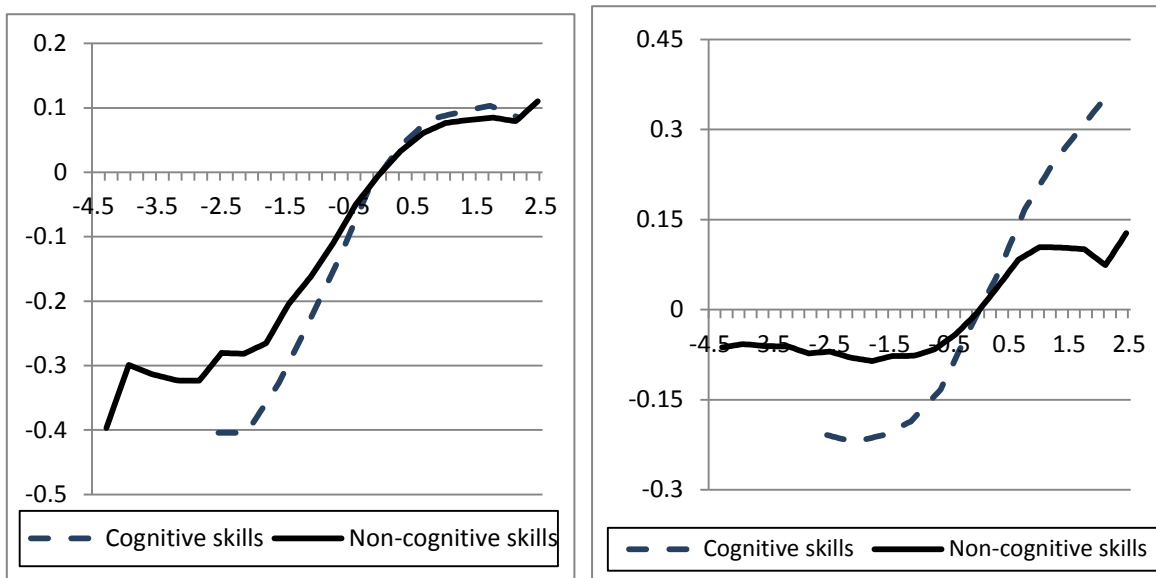
Figure 3. Inactivity and skills



Panel A. Cognitive skills

Panel B. Non-cognitive skills

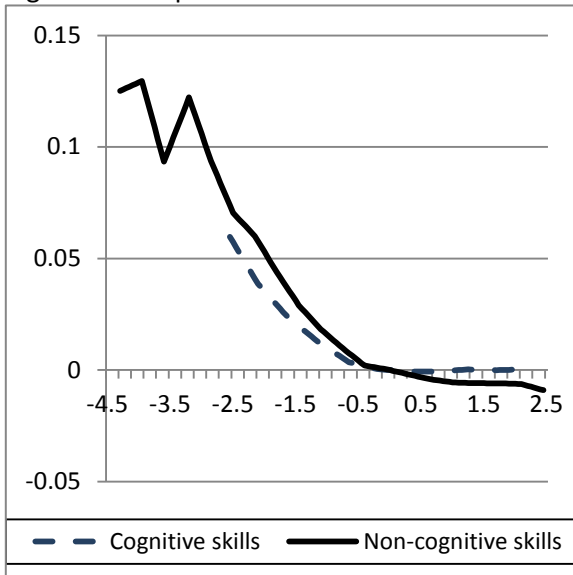
Figure 4. Non-parametric effects of skills on education outcomes



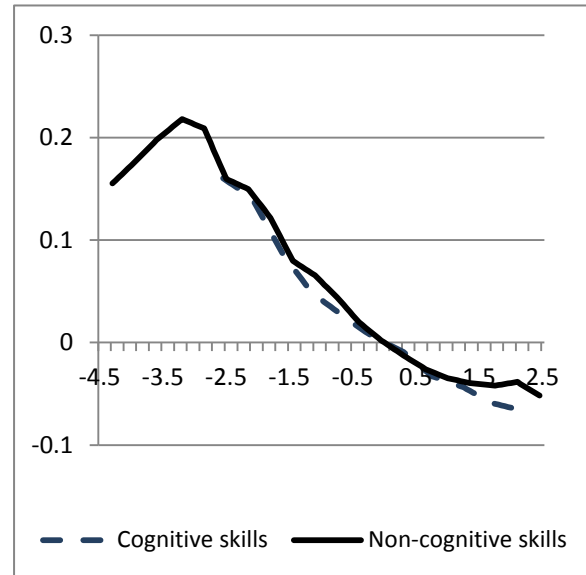
Panel A. High school graduation

Panel B: College enrollment

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



Panel A. On welfare



Panel B: NEET

Appendix Table A1. Descriptive statistics and full model results

| | (1) | (2) | (3) | (4) |
|---|--------------|------------------------|----------------------|----------------------|
| | Mean values | Graduation | On welfare | NEET |
| Cognitive skills | 0.00 [1.00] | 0.130* (0.00171) | -0.0038* (0.0004) | -0.0399* (0.0019) |
| Non-cognitive skills | 0.00 [1.00] | 0.117* (0.00170) | -0.0196* (0.0007) | -0.0549* (0.0021) |
| Female | 0.49 | 0.00587* (0.00226) | 0.0080* (0.0006) | 0.0151* (0.0027) |
| First generation immigrant | 0.03 | 0.0454* (0.00723) | -0.0133* (0.0025) | -0.0029 (0.0091) |
| Second generation immigrant | 0.02 | 0.0515* (0.00825) | -0.0182* (0.0019) | -0.0130 (0.0100) |
| Parents' highest educational level is high school education | 0.47 | 0.0437* (0.00358) | -0.0117* (0.0013) | -0.0230* (0.0044) |
| Parents' highest educational level is bachelor degree | 0.29 | 0.0577* (0.00385) | -0.0095* (0.0013) | -0.0219* (0.0047) |
| Parents' highest educational level is master or PhD | 0.1 | 0.0418* (0.00452) | -0.0059* (0.0013) | -0.0173* (0.0055) |
| Benefits due to disease before the age of 18 | 0.02 | 0.0108 (0.00835) | 0.0005 (0.0030) | 0.0142 (0.0112) |
| Benefits due to disabilities before the age of 18 | 0.02 | -0.0557* (0.00774) | 0.0127* (0.0029) | 0.0661* (0.0105) |
| One parent employed | 0.24 | 0.0399* (0.00546) | -0.0258* (0.0026) | -0.0295* (0.0071) |
| Both parents employed | 0.71 | 0.0706* (0.00555) | -0.0337* (0.0025) | -0.0582* (0.0072) |
| Parental income in 100,000 NOK | 6.05 [3.98] | 0.00120* (0.000328) | -0.0004* (0.0001) | -0.0014* (0.0004) |
| Parental income in 100 NOK squared | 52.5 [995.2] | -0.0023* (7.72e-07) | 0.0000* (0.0000) | 0.0000 (0.0000) |
| Married parents | 0.61 | 0.0511* (0.00262) | -0.0113* (0.0008) | -0.0196* (0.0031) |
| Divorced parents | 0.12 | 0.00619 (0.00349) | -0.0035* (0.0012) | -0.0029 (0.0045) |
| Mobility | 0.11 | -0.0439* (0.00344) | 0.0143* (0.0013) | 0.0264* (0.0040) |
| Mobility unknown | 0.02 | -0.00931 (0.00879) | -0.0008 (0.0028) | 0.0280* (0.0108) |
| Born second quartile | 0.27 | 0.00912* (0.00268) | -0.0007 (0.0007) | -0.0060 (0.0033) |
| Born third quartile | 0.26 | 0.0228* (0.00274) | -0.0011 (0.0007) | -0.0098* (0.0031) |
| Born fourth quartile | 0.23 | 0.0297* (0.00289) | -0.0028* (0.0008) | -0.0098* (0.0033) |
| Observations | 154,515 | 154,515 | 154,515 | 99,940 |
| R-squared | - | 0.299 | 0.070 | 0.073 |
| Cohort x 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 percent level.