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Effect of Secondary Education on Cognitive and Non-cognitive Skills *

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Abstract

We exploit admission cutoffs to secondary schools to study the effects of general academically oriented, versus vocational secondary schooling on cognitive and non-cognitive skills using a regression discontinuity design. We measure these skills using the Finnish Defence Forces Basic Skills Test that due to compulsory military service the vast majority of Finnish men take and that is a strong predictor of later labor market success. We find that the large differences in the average skills across students that differ in their schooling when entering military service are due to selection rather than causal effects of secondary schooling on either cognitive or non-cognitive skills.

Keywords: non-cognitive skills, regression discontinuity, secondary schooling

JEL Codes: J24, I21

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1 Introduction

The importance of both cognitive and non-cognitive skills in the labor market is now a widely accepted fact. Both cognitive and non-cognitive skills affect employment and earnings and explain an empirically important fraction of variation in labor market success between individuals. There is also evidence suggesting that the importance of non-cognitive skills in particular has grown over time.[1]

Prior literature has convincingly shown that early education interventions can have positive effects on cognitive and non-cognitive skills (e.g. (Almlund *et al.*, 2011); (Currie & Almond, 2011)). There is also some evidence showing that large-scale reforms affecting education at a later age may improve cognitive skills (e.g., Brinch & Galloway (2012); Pekkala Kerr *et al.* (2013)). This paper contributes to the scarce literature by using the admission cutoffs in secondary education to identify the causal effects of type of secondary education, general versus vocational, on both cognitive and non-cognitive skills.

Whether to train adolescents with general skills or with skills that are relevant for specific occupations is one of the key questions that governments around the world struggle when trying to respond to challenges imposed by rapid technological change (Hanushek *et al.* (2017); McNally *et al.* (2022)). The critics of vocational education argue that general education provides broader knowledge and basic skills that better serve as foundation for further learning and adopting to new technologies. This hypothesis has motivated much of the research on the returns to vocational education but there is no direct evidence on the effects of type of education on skills. To the best of our knowledge, we are the first admission discontinuities to identify the effect of schooling on skills.

This paper studies the effects of general vs. vocational education on both cognitive and non-cognitive skills measured in the Basic skills test of Finnish Defence Forces. We use data on Finnish men born between 1974 and 1979 who apply to secondary school between 1991 and 1995, and perform their military service between 1995 and 1999.

[1] For an authoritative survey see e.g. Cunha *et al.* (2006). On trends, see Edin *et al.* (2022)

Finland is one of the few western countries where military service is still compulsory. Consequently, the vast majority of Finnish men enter military service and are tested at the beginning of service, typically at age 19 or 20. Access to military test data therefore provides us with an extensive test battery of both cognitive and non-cognitive skills for almost entire cohorts of young men. We also demonstrate that these skills are highly relevant in the labor market by showing that the military skill test scores are strongly correlated with later earnings.

To identify the effects of general versus vocational secondary education, we use regression discontinuity design (RDD) and exploit admission thresholds to the general secondary schools in the Finnish centralized admission system. The two education tracks provide students with very different curricula and focus. General secondary schools have an ambitious academic program that prepares the students for tertiary education. Vocational secondary schools, on the other hand, specialize in practical skills needed in specific occupations. Both secondary education tracks include some academically oriented studies, but their weight is much larger in the general secondary schools.

By the time Finnish men enter military service and take the battery of psychological tests they have spent three years in a school environment that dramatically differs by school assignment at age 16. For the applicants at the margin, this assignment is essentially random which allows identification of causal effects of schooling at ages between 16 and 19 on cognitive and non-cognitive skills of young men.

Our data show that there are large differences in both cognitive and non-cognitive skills between the men that have obtained general and the men that have obtained vocational secondary school degrees at the time they enter military service. Average cognitive skills of general secondary school graduates are 1.1 standard deviations higher than average cognitive skills of vocational school graduates. The corresponding difference in non-cognitive skills is .6 standard deviations.

Our results indicate that these skill differences are almost entirely due to selectivity and that the type of secondary schooling has surprisingly little effect on either cognitive or non-cognitive skills. In particular, we find no effects on the skills that are most highly correlated with future earnings, such as logical, mathematical or verbal reasoning or measures related to sociability, achievement motivation and self-confidence. Interestingly, we observe that admission to general secondary school, or perhaps greater exposure to female classmates, decreases measures of masculinity.

Our paper is related to several strands of previous literature. The effect of schooling on cognitive skills is an old question. In their controversial book "The Bell Curve "(Herrnstein & Murray, 1994), the authors provide an extensive literature survey and claim that cognitive skills are largely inherited and only to a limited extent affected by schooling or training interventions after early childhood. Other reviews, based on largely same sources reach an opposite conclusion (Winship & Korenman, 1997), and for example Hansen *et al.* (2004) find substantial effects of schooling on measured abilities. Still, in their handbook chapter Almlund *et al.* (2011) note that there is surprisingly little direct evidence on the effect of schooling on cognitive skills (and on personality traits). More recent quasi-experimental evidence tends to find positive effects of schooling on cognitive skills, both for measures of fluid and crystalized intelligence (see Carlsson *et al.* (2015) as an example with similar outcome measures to this study and see Ritchie & Tucker-Drob (2018) for a meta-study of quasi-experimental results).

Direct evidence on the effects of schooling on non-cognitive skills is even more limited than evidence on the effects on cognitive skills. As noted by Almlund *et al.* (2011) non-cognitive skills may be more malleable also at later ages and affected by life events such as marriage, entry to labor market and education, while cognitive skills would be more or less set at ages around ten. However, empirical evidence on the effects of education after early childhood on non-cognitive skills is still scarce (See Schurer (2017) for a survey).

Admission thresholds have been used in earlier work to study the effects of educational programs on labor market performance. Kirkeboen *et al.* (2016) examine the effects of field of study at university whereas Silliman & Virtanen (2022), Brunner *et al.* (2021), and Dahl *et al.* (2023) study the effects of secondary school programs on earnings. In these papers the effect of education program on skills is one of the potential mechanisms, but the effect on earnings may also be due to subsequent educational and occupational choices, for example. [2] In addition, Barrera-Osorio *et al.* (2020) uses experimental design to study the effects of job training program curricula on earnings. They find that the vocational programs that emphasize technical skills relative to social skills experience greater returns, but only in the short run. Our paper differs from the previous work in that it provides direct information on the effect of schooling on skills and, in particular, also on the non-cognitive skills.

The rest of the paper is organized as follows. In the following section, we describe institutional background related to the Finnish school system and military service in detail. Section 3 presents the data and descriptive statistics. In section 4, we describe our identification strategy and in section 5 we present the main results. Section 6 concludes the paper.

2 Institutional background

2.1 Finnish secondary schooling system

Our study focuses on men born between 1974 and 1979 who apply to secondary education in the beginning of 90s. In the following, we describe the education institutions relevant for these cohorts.

Compulsory comprehensive school lasts for nine years in Finland. The comprehensive school usually ends in May of the calendar year when the students turn sixteen, after which most students apply to secondary education.

There are two main options at the secondary level. The general secondary schools (lukio) offer an ambitious academic program that prepares students for tertiary education either

[2] Brunner *et al.* (2021) also report results on test scores, but they are not comparable across education programs.

in the traditional universities or in the universities of applied sciences. Completing general secondary education requires passing 75 courses each consisting of 38 hours in class plus homework. The target duration is three years, but students can study at their own pace and some graduate only after four years. The general secondary school ends in the matriculation examination that provides general eligibility to university-level studies but no professional qualifications.

General secondary school students study Finnish, math, natural sciences, humanities and, on average, 2.5 foreign languages. In contrast to some countries, the general secondary schools offer a relatively uniform program. The students can choose by level of difficulty and the number of elective courses in math; they can choose foreign languages based on selection offered by their school; they have both compulsory and voluntary courses in humanities and natural sciences. Still, there are no separate tracks in general secondary school(National Board of Education (1994b)).

The other secondary education option is vocational education that provides practical training and vocational competences in specific occupations. The most common fields in applications of the men in our sample were electrical and automation technology (18.8%), sales and marketing (16.5%), motor vehicle technology (13.6%), construction (8.9%), and metalwork and production technology (8.6%). In vocational education over 80% of training is concentrated on practical skills. A part of training training takes place at workplaces under supervision of a more experienced worker.

Vocational education also contains compulsory classes in Finnish, math and one foreign language but compared to general education these classes are much more limited. For the cohorts that we study, a three-year vocational program consisted of 120 study weeks out of which only 20 study weeks were general studies that include, for example, compulsory Finnish and math classes. Based on the 1995 curriculum, we estimated that the minimum requirements in general secondary education contain 2.4 times more Finnish classes, 3.2 times more math classes, 5.9 more foreign language classes and 24 times more classes in the sciences and humanities than the minimum requirements in vocational education. An alternative comparison by the National Board of Education notes that the learning goals for Finnish and math in vocational education are both roughly equivalent to the content of three general secondary school courses while in the general secondary school the minimum requirement are six courses for both courses. This official comparison hence displays smaller differences than our calculation based on fraction of Finnish and math out of total compulsory courses but nevertheless demonstrate a radically different content of practically-oriented vocational education and more theoretically-oriented general education (National Board of Education (1994a)).

Vocational education is more popular among boys than among girls. In 1995, approximately 45% of the boys who were enrolled in secondary education were in vocational education and the rest, 55% in general education. The corresponding figures for girls, are 23% and 77%, respectively .

2.2 Applications and admission to secondary schools

Application to secondary education takes place through a centralized application system maintained by the Finnish National Board of Education.[3] Students can apply to up to five different school-program combinations. Admission is based on school and program -specific admission scores.

For most general programs admission is based on arithmetic average in theoretical subjects (excluding, for example, arts and physical education). Grades, and accordingly the grade point average, are on scale from 4 (failed) to 10 (excellent) with averages recorded at two decimal points and possible ties broken by lottery.

Vocational schools typically have several education programs per school and use program-specific admission criteria. Although, compulsory school GPA is also the main criteria for admission in vocational programs, they apply slightly different scales, giving different weights

[3]For reference, the description of the institutional context in this paper is based on the description in Huttunen *et al.* (2023).

to different grades, and in some cases supplement GPA with other criteria for admission (for example, work experience and aptitude tests).[4]

The students apply to secondary education in February-March of the final year of comprehensive school. Students receive their final grades only in May and, thus, do not know their exact admission points at the time of applying. There is also annual variation in the admission cutoffs which adds to the difficulty of strategic application behaviour.

The supply of slots in each educational program is fixed and announced before the application process begins. Applicants are allocated to schools using a DA algorithm (Gale & Shapley, 1962) that takes into account the preferences of the applicants and the selection criteria of the schools. The algorithm terminates when every applicant is matched to a program or every unmatched candidate is rejected by every program listed in her application.

At the end of this automated admission stage, in June, applicants receive an offer according to the allocation result. Admitted applicants have two weeks to accept their offer, while the rejected applicants are placed on a waiting list in rank order based on their admission scores. After these two weeks schools start to fill their remaining vacant slots by inviting applicants on their waiting list in the rank order within each program. This updating process affects roughly 10 percent of applicants in our period of study. We define the admission cutoffs based on the last admitted applicant to each program.

This paper focuses on applicants who are at the margin of being admitted into general secondary school programs. At the time when cohorts in our sample applied to secondary education, there were 456 general secondary schools in Finland, each with potentially different admission threshold. The entry requirements to the general secondary schools are, on average, substantially higher than the entry requirements to vocational programs. Hence, applicants who have listed vocational schools in their application, are typically admitted to vocational school if they fail to gain access to a general program.

The main educational option for those not accepted to any secondary education programs

[4] In our data, we do not observe the weighting of the grades nor the points for these different admission criteria. Therefore, we focus on admission into the general track.

is an additional 10th grade of comprehensive school which students can use to improve their grades. Most initially rejected students re-apply to secondary education in the following years. However, as they have already completed their compulsory schooling, they are under no obligation to continue in education.

2.3 Military service

According to the Conscription Act, all Finnish men have to participate in either armed or unarmed military training or non-military (civil) service. Women can apply to military service on a voluntary basis. In the years that we examine, the duration of armed military service was either 8 or 11 months (those trained as officers spent longer in service). Non-military service lasted for 12 months.

All Finnish men are called to the draft in the fall of the year they turn 18. At this point they are assigned a starting date and location where to report for service. In most cases men enter service during the two calendar years after the draft year, at age 19 or 20. However, it is possible to request for a postponement of the service (due to on-going education, for example), or to apply to enter the service as a volunteer already at the age of 18.

The draft includes a physical examination. Those not fit for service can be exempt either temporarily or permanently. It is also possible to be exempt due to religious or ethical conviction.

3 Data and descriptive statistics

3.1 Test data

Data on the cognitive and non-cognitive skills used in this study are obtained from the Basic Skills Test of the Finnish Defence Forces. All conscripts are tested during the first weeks of their military service with a battery of cognitive and non-cognitive skills tests. The test is conducted at the military base in standardized conditions. No test data exists on men that are exempt from service or on men that enter civil service. At the time of the test the conscripts are typically 19 or 20 years old.

Between 1996 and 1998 the non-cognitive part of the test was conducted already at the draft with the intention that it could be used in task placement during military service. The process turned out to be too slow and conditions at testing sites not sufficiently comparable and therefore the Defence Forces reverted back to the practice of testing conscripts at the beginning of service. (Nyman, 2007)

During the period covered in our data, 70% of men performed military service and took the skill test battery. Sample is somewhat selective, as men with lower comprehensive school GPA are less likely to perform military service and to take the Basic Skills test. However, as we demonstrate later in Table 3, admission to the general secondary school has no effect on the likelihood of entering military service and hence selectivity is not causing a bias in the results. Given that about 70% men are in the data, the sample includes most of the eligible male population with the exception of those with weakest school performance.

The test contains two main sections: one for the cognitive and one for the non-cognitive skills. The cognitive skills test resembles aptitude tests used in college admissions (SAT) and is very similar to the ability test used in Swedish military described in, for example, Grönqvist *et al.* (2017). It has three forty-question sets that measure verbal and numerical skills and logical reasoning. The logical reasoning part that is based on Raven's progressive matrices is closely related to common IQ tests.

The non-cognitive test section was developed by the Finnish Defence Forces in late 1970's. It has been used in an unchanged format from 1982 to 2001 (covers all the years that we examine). Also this test has several parts. We use data from the leadership inventory which contains measures of eight traits that the army psychologists have judged to be important characteristics for the military leaders and that the Defence Forces use in allocation to different types of military training.[5] Each trait is measured with 20 to 30 statements with

[5]In addition the test contains a section based on Minnesota Multiphasic Personality Inventory (MMPI) that is used for screening for mental health conditions.

which the test-taker is asked to agree or to disagree. The individual test items are not published and detailed content of test is a military secret.

The test battery is rather extensive. The cognitive test has 120 items and the leadership inventory part of the non-cognitive test has 218 items. In the years 1982 to 2000 that we use in this study, the test was a paper and pencil test that took about two hours to complete. We have access to raw test scores i.e. number of correct answers in the cognitive test and trait indicative responses in the non-cognitive tests but not to the individual test items.

The Defence Forces use the test results as one of the criteria when selecting conscripts to officer training. According to a validation study (Nyman, 2007), the test scores are correlated with other assessments of performance during military training and predict scores in final evaluations conducted after officer training.

More importantly for this study, the military test scores are also strongly correlated with various labor market outcomes. Jokela *et al.* (2017) demonstrate that men scoring higher in the military tests are more educated and earn substantially more between 30 and 34 years of age. Jokela *et al.* (2017) also validate measures of the leadership inventory against the more commonly used personality test BIG5 by administering short versions of both tests to a sample of students. According to their results, subscales of the test are highly correlated with measures of extroversion, neurotism and conscientiousness in BIG5.

Psychological test scores have no natural scale. The defence forces aggregate the raw scores to measures of cognitive and non-cognitive skills and use a standard nine point scale for the both measures. To make the interpretation easier we convert the raw scores to more familiar standard deviation units so that each dimension has mean zero and standard deviation one in the cohorts that we use in the analysis. In practice, we use a confirmatory factor analysis to estimate factor loadings between the observed raw scores and latent factors, and well as, to estimate correlation between the latent factors in a two factor model and then estimate factor scores that we use as outcome variables (details in the appendix). After standardization, these factor scores have mean zero and standard deviation one.

The factor analysis approach reduces dimensionality and rescales the test scores. Factor scores are re-scaled weighted averages of raw scores with weights based on estimated factor loadings. As an alternative dimension reduction approach, we follow the example in Cunha *et al.* (2010) and anchor the test scores to later earnings data. In this approach, we regress earnings at age 35 - 39 on the raw test scores and use predicted values from this regression as skill measures. This procedure weights the raw scores in a different way than factor analysis. In addition to reducing dimensionality, the procedure generates a meaningful scale for the outcome variables. Results based on anchored test scores are presented in the appendix.

3.2 Data on earnings and education

Our earnings data are based on tax records available from 1987 onward. We define earnings based on annual wage earnings excluding taxable benefits. We link the tax data across years and to the other data sources by using person ids. For the main part of our analysis, we use average log annual real non-zero earnings at ages between 35 and 39 i.e. at an age when annual earnings are highly correlated with lifetime earnings (Böhlmark & Lindquist, 2006). We take an average over five years to reduce the effects of random fluctuations and issues with zero earnings during periods outside the labor force.

Education data comes from two main sources. Data on completed degrees are based on Statistics Finland Register of Degrees and Examinations that covers all post-compulsory degrees completed in Finland. Furthermore, from Joint National Application Register maintained by National Board of Education, we have information on applications and admissions to secondary schools, as well as on grades from comprehensive school. However, the data does not include information on admission criteria that are used in vocational education (see Section 2.2. Therefore we focus solely on the effects of admission to the general tracks.[6]

We use Statistics Finland family relation tables to link the men in the sample to their parents. Information on completed education and earnings of the parents is based on the

[6]We have no high-quality data on enrollment in these years that would allow to identify effects of years at school in a reliable way.

same registers as information on education and earnings of the men in the sample.

3.3 Estimation sample

We restrict our estimation sample to conscripts who take the Basic Skills Test in the year when they are between 18 and 22 years old. This omits those who postpone their service due to participation in college-level education and hence take the test after college (about 4% of men take the test at age higher than 22) and naturally those who are exempt from military service or enter civil service (about 15% of men in our data do not have a valid test score). Note, however, that the data also include most college students, since most men perform military service before starting in college.

We also exclude the Swedish-speaking minority from our analysis. Swedish-speakers typically attend different schools and take the test in Swedish and are therefore not strictly comparable. As only about 5% of conscripts are Swedish-speakers, removing them from the sample has no effect on our main results.

The results from the full Basic Skills test are available from the year 1982 onward while the non-cognitive skills test was adopted up to the year 1999 after which the test was reformed. Cognitive test results also exist for the later years, but Defence Forces have not released data on the new non-cognitive test that was adopted in 2000.

Data on the application register is available from 1985, 1989 and annually from 1991 onward. Due to changes in the vocational education system, the observations from the 1980s may not be fully comparable with the later years. Therefore, we only use data from 1991 onward.

To maximize the sample size while maintaining comparability, we restrict data on cohorts who applied to secondary school in the years from 1991 to 1995 ($\sim$ 426,000 individuals). The men in our final data are born between 1974 and 1979 and perform their military service between the years 1992 and 1999. As we study the effects of general secondary schools, the sample is further restricted to those who applied to general education (47% of applicants).

Additionally, we make the following restrictions to our estimation sample. First, we focus on first time applicants who are between 15 and 17 years of age when applying to secondary school (most applicants are 16 years old). Second, we exclude programs that do not reject any applicants as there is no relevant cut-off score to be exploited. Finally, we need at least two applicants on each side of the cutoffs for our RDD design, so we exclude programs that do not meet this requirement as well as applicants to these programs. Our final estimation sample has 41,164 male applicants in 1144 program-year combinations.

3.4 Association between the test scores and earnings

To demonstrate the relevance of skill measures, we examine their predictive power for future earnings. In practice, we calculate the log average earned real income between ages 35 and 39 and then regress this earnings measure on all cognitive and non-cognitive test scores, as well as, on the cohort dummies.[7]

In Table 1, we report the results from these regressions. In the first column, we explain average earnings with the scores in the three subsections of the cognitive test. We have access to the raw scores i.e. the number of correct answers in each test, but for easier interpretation we have normalized these scores to have mean zero and standard deviation of one and use these normalized scores as explanatory variables in this regression.

The cognitive test scores have a substantial effect on earnings. In particular, the arithmetic test scores are highly predictive of later earnings. One standard deviation increase in the arithmetic test increases earnings at ages 35 to 39, ceteris paribus, by 12.5 percent. Also the partial correlations of both the visuospatial and the verbal tests are positive and statistically significant. Jointly the three cognitive test scores explain 3.9 percent of the variation in earnings at ages between 35 and 39.

In the second column, we repeat the exercise using the non-cognitive test scores. Also these scores display a strong correlation with future earnings. In particular, measures related

[7] As noted by Jokela *et al.* (2017) both cognitive and non-cognitive test scores improve over time reflecting a phenomena known as the Flynn effect

to achievement motivation and self-confidence are highly correlated with future earnings. Predictive power of the non-cognitive test scores is only slightly lower than that of cognitive skills.

In the third column, we include both the cognitive and the non-cognitive test scores as explanatory variables. The measures are generally positively correlated and therefore coefficients of individual measures smaller than in columns 1 and 2. Coefficients of most cognitive test scores and most non-cognitive scores remain significant even in the regression where both scores are simultaneously included. Jointly the test scores explain about 5 percent of variance in earnings measured 15 to 20 years after taking the test.

Finding that both cognitive and non-cognitive skills measured in tests taken before entry to labor market or college-level education explains a substantial fraction of the variance in earnings is interesting but not a particularly new finding. Numerous studies have reported similar results (See for example, (Borghans *et al.*, 2008; Kautz *et al.*, 2014; Jokela *et al.*, 2017; Edin *et al.*, 2022).

3.5 Descriptive statistics

Figures 1 – 3 plot the test scores by educational background at the time of taking the test. In these figures, we restrict our estimation sample to include persons who were aged 18 to 22 at the end of the year when they take the test. For easier interpretation and readability, we display smoothed standardized scores that are scaled to mean zero and standard deviation one in pooled data. In Figures A1 and A2 in the appendix, we also report the distribution of raw scores by the level of completed education. In most, but not all dimensions, these raw scores are roughly normal. The raw scores also reveal that the test is sufficiently challenging so that the ceiling effects are not an important issue in the cognitive scores, but limit the range of scores in some but not all sections of the non-cognitive test.

Figure 1 reveals large differences in skills across men with different education at the test date. The men who have completed general secondary education by the time of the test have much higher scores in both cognitive and non-cognitive tests than men who have completed a vocational degree or have no post-compulsory degree by the test date. On the other hand, the differences between men with vocational education and men with no completed education by the time of entering the military service are small. The differences in the cognitive skills across men with different schooling is substantially larger than the difference in the non-cognitive skills.

In what follows, we focus on the differences between men with general secondary education and the two other groups pooled together. This is also the only margin where we can observe exact admission criteria required in the regression discontinuity design.

Figure 2 displays the differences in the three components of the cognitive skill test and Figure 3 in the eight components of the non-cognitive skill test. We find large differences in the cognitive skill distribution between those admitted to the general secondary schools and the other two groups. The differences are of roughly equal magnitude (about 1 standard deviation) in all three components of the cognitive skills test.

Figure 3 demonstrates that there are also large differences in several non-cognitive traits across education groups. Those who have completed general secondary education have substantially higher scores in measures related to motivation (leadership motivation and achievement motivation) but also in self-confidence, deliberation, sociability and dutifulness. As all these skills are highly correlated with observed earnings, those with general secondary education clearly are in an advantageous position. On the other hand, no major differences in skills can be detected between those with vocational education and those with no completed education after the comprehensive school.

Table 2 reports the means of the key variables used in the analysis. In addition to the differences in test scores displayed in Figures 1 – 3, there are large differences in student characteristics across schooling levels. Men who have completed general school have a substantially higher grade point average in comprehensive school than men with a vocational degree or no degree (8.3 vs. 6.7 or 6.5 on scale from 4 to 10). General school graduates have more educated and higher earning parents. The general secondary school graduates also have some 50% higher earnings at age 35 to 39 than the men in the other two groups.

4 Identification strategy

4.1 Empirical specification

Identifying the effects of education on skills is challenging for at least two reasons. First, education may foster skills, but skills may also affect educational aspirations and admission prospects to different schools. Solving this reverse causation issue requires some variation in education that is not affected by skills. Second, educational choices are likely to be correlated with various factors that are also correlated with skills (e.g. parent characteristics). Some of these factors can be controlled for, but not all background characteristics can be measured in a reliable way. The resulting omitted variable problem generates a bias in the estimates.[8]

We identify the effects of admission into general secondary education on the cognitive and non-cognitive skills by using admission cutoffs in a regression discontinuity design. As discussed in Section 3.3, we restrict our estimation sample to individuals who applied to at least one general secondary school and compare the scores of each applicant to the admission threshold of the general secondary school with the lowest GPA requirement among the general programs listed in his application. By construction each applicant is in data only once. We then compare the outcomes of students who have very similar admission scores but narrowly ended up on different sides of each cutoff and were therefore either admitted to the general track or not. As we demonstrate below, the applicants who are barely accepted and those who are just rejected are very similar in all the dimensions that we can measure. Given that for these applicants, the admission cutoffs are as good as random, there is no reason to expect differences in unobserved dimensions either.

[8]Table A2 summarizes OLS estimates of the effect of graduating general secondary school on the test scores using different the sample restrictions and control variables. In general, the OLS estimates show much larger effects on the test scores than the RDD estimates.

The applicants scoring above the general school admission cutoffs have much higher probability of being admitted to at least one general secondary school. As shown in Figure 4, being above the admission cutoff increases the likelihood of being admitted to a general school by approximately 65 percentage points. The fuzziness of our setting is due to several reasons. Firstly, the applicants above the general school admission cutoffs can still be admitted to the vocational track instead, if they have ranked a vocational program higher in their application and pass the threshold of this vocational program. [9] Secondly, our data only has information on the final admission decisions, and we do not observe the offers that applicants decline. Furthermore, some of the applicants in the waiting list could not be contacted due to the way in which these offers were made. To account for the fuzziness in the admissions, we also report results from an instrumental variable strategy, where we scale the reduced form results by the jump in admission probability (see discussion below). Those below the admission cutoffs are admitted to vocational secondary education or fail to gain access to secondary education altogether.

We define the cutoff for each school k in each year t as the GPA of the last accepted applicant. Our running variable for applicant i is simply the difference between the applicant GPA and the admission cutoff in the program he applied to:

$$r_{ikt} = c_{ikt} - \tau_{kt}, \tag{1}$$

where c_{ikt} is the applicant's GPA and τ_{kt} the cutoff to school k in year t.

To identify the effect of being above the cutoff on cognitive and non-cognitive skills, we pool data on each school and year (altogether 1144 separate thresholds), and estimate the following reduced form regression[10]:

[9] As discussed in Section 3.2 we only observe GPA, and have no information on other admission criteria that are used in vocational education. Therefore, we are unable to determine the applicants' admission success in the vocational programs. However, dropping all applicants who had ranked at least one vocational program above the least selective general program had no effects on the results.

[10] Since we are unable to detect how applicants perform with respect to the admission cutoffs in voca-

$$y_{ikt} = \alpha_{kt} + \beta Z_{ikt} + (1 - Z_{ikt}) f_0(r_{ikt}) + Z_{ikt} f_1(r_{ikt}) + \Gamma' X_i + e_{ikt}, \tag{2}$$

where y_{ikt} is the test score for applicant i to track k in year t. Z_{ikt} is an indicator variable for being above the cutoff, and r_{ikt} is the running variable centered at the cutoff (value 0). We allow the slope of the running variable (f_n) to differ on either side of the cutoff. We include fixed effects for each cutoff and their interactions with the running variable. The standard errors are clustered at the cutoff level. X_i is a vector of control variables that includes birth year fixed effects and the first and second polynomials of age at test measured in days. Between 1996 and 1998, the non-cognitive test was conducted at the draft instead of after entering military service. Since the two testing sites may not be entirely comparable, X_i also includes a dummy indicating if the individual took the non-cognitive test at the draft.

We also employ an instrumental variable strategy (fuzzy RDD) to convert the reduced form estimates to local average treatment effects (LATE) of general secondary schooling on the cognitive and non-cognitive skills. We report results of two separate specifications using either admission to a general secondary school or completing a general secondary school degree by the time of taking the test as the treatment variable D_i. In both cases crossing the admission threshold is used as an instrument The first stage of this fuzzy RD design is Equation 2 where the outcome variable is D_i.

We estimate Equation 2 using non-parametric local linear regression with triangular kernel weights:

$$K(r_i) = (1 - \frac{r_i}{h}) \mathbb{1}(\frac{r_i}{h} \leq 1), \tag{3}$$

tional schools, we are not able to fully account for the application preferences as suggested suggested in (Abdulkadıroğlu *et al.*, 2022). With this exception, we follow their approach.

where h is the bandwidth determining the observations that are sufficiently close to the threshold to be used in estimating the effect of admission. We estimate the optimal bandwidth using the selection procedure in Calonico *et al.* (2014). However, to make estimates with different outcomes comparable, we use a bandwidth of 0.5 GPA units in all baseline specifications. [11]

Figure 5 illustrates the effect of exceeding the admission threshold on completed degrees. The likelihood of completing general secondary education by the time of entering military service increases with comprehensive school GPA. However, there is a clear discontinuity at the admission threshold of the general secondary school (dashed line in the figure). Some students who score below the threshold still enter general secondary school later, e.g. by re-applying in the following years. Also some students above the admission threshold never complete general secondary school or at least have not done so by time of entering military service. Some of these students are admitted but drop out of the program at some stage. Others have ranked a vocational program higher in their secondary school application and hence end up in vocational school even though they could have also been admitted to general secondary school.

The middle panel of Figure 5 shows the likelihood of completing a vocational school as a function of comprehensive school GPA. This is a mirror image of the left panel. The likelihood of completing vocational training decreases with the comprehensive school GPA and displays a clear drop at the entry threshold to general secondary school. The rightmost panel of Figure 5 confirms that exceeding the admission threshold of general secondary school mainly affects the type of school rather than amount of schooling. Exceeding the admission threshold has no effect on the likelihood of completing some secondary education.

[11] Optimal bandwidths vary between 0.3 and 1.3 depending on the outcome. In general, the optimal bandwidths are lower below than above the admission thresholds. Table A4 presents RDD estimates on our main outcomes of interest. Our main results are largely unaffected by the choice between the optimal bandwidths or a fixed bandwidth of .5 GPA units. In Figure A5, we also test different fixed bandwidth choices. Our results are not sensitive to the choice of bandwidth, unless we use the very smallest bandwidths.

4.2 Validity of research design

The application and admission process in Finland provides an attractive setting for our study. The timing of the application process (that applicants do not know even their own grades at the time of applying) as well as the DA algorithm provides a little opportunities for strategies behavior. We perform also various empirical checks to study the validity of the research design.

In Table 3, we verify the validity of our approach by examining the effect of exceeding the admission threshold on several pre-determined variables. According to these results, our treatment is uncorrelated with parents' education and living in an urban area. However, there is a discontinuity in father's earnings at the cutoff that is significant at the 10% level. Adding controls for parents' earnings and education does not change our results (we report these in the Appendix). For a summary measure capturing the effect of all pre-determined variables, we regress test scores on all pre-determined variables listed in Table 3 and take the predicted value of this regression. This summary index seems to be well balanced around the admission threshold.

We also check that exceeding the admission threshold has no significant effect on the likelihood of entering military service (and taking the test) or on the age at which the test is taken.

In the middle part of Table 3 we show that exceeding the admission threshold has a large effect on the school environment. Average peer GPA increases by almost one unit (roughly one standard deviation). The share of women among classmates increases by 15pct. Exceeding the admission threshold also significantly increases the average test scores of classmates. Finally, crossing the threshold significantly increases 'peer quality' measured by parents' education and earnings.

In the bottom section of Table 3, we confirm the results already illustrated in Figure 5. Exceeding the admission threshold increases the likelihood of completing general secondary school by about 20pct and has roughly equal negative effect on the likelihood of obtaining a vocational secondary degree. Hence, exceeding the threshold mainly affects the type of education and has no significant effects on completing secondary school by the time of entering military service. As the main purpose of general secondary school is to prepare students for higher education it is not really surprising that exceeding the threshold increases the odds of later completing a tertiary degree. For those admitted at the margin, this increase mostly reflects an increase in the likelihood of completing a polytechnic degree at the universities of applied sciences rather than a degree in the traditional universities.

An increase in the likelihood of entering tertiary education is also reflected in the effect on later earnings. Earnings are reduced at ages 20 to 24 when those who enter tertiary educational institutions are mostly still at school, and at ages 25 to 29 when tertiary graduates have just entered the labor market. After these ages, the effect on earnings decreases and approaches zero by age 39. This finding is roughly in line with findings of Silliman & Virtanen (2022) who use same data for more recent cohorts to evaluate the effect of schooling on earnings.[12]

Additionally, we test for possible manipulation in the running variable. Figure A4 in the Appendix report GPA histograms. Figure A4(a) shows that there is a noticeable spike at the cutoff which is also confirmed by the density test proposed by (Cattaneo *et al.*, 2020). However, since the cutoffs are defined by the last admitted applicant to each program, this spiking at the cutoff is mechanical in nature. When we exclude these marginal applicants in Figure A4(b), the spike disappears and the sample passes the density test. To ensure that our main estimates are not sensitive to the inclusion of the applicants used to define the cutoff, we present donut RDD estimates in Table A5 in the Appendix. These results are similar to our main estimates.

[12]The set-up in Silliman & Virtanen (2022) is slightly different as they compare vocational secondary education to general secondary education while we compare general secondary to all others including the group that quits school after compulsory comprehensive school. Exact replication of Silliman & Virtanen (2022) is not possible for the cohorts we use in this paper (and for whom military test scores are available) due to lack of data on exact entry criteria used by vocational schools.

5 Main results

In Figure 6, we show the effect of schooling on skills - the main question analysed in this paper. The cognitive and non-cognitive skills are both positively correlated with comprehensive school GPA, and the correlation is stronger for the cognitive skills. However, based on Figure 6, admission into general secondary education has little, if any, effect on cognitive and non-cognitive skills. There is a visible yet economically insignificant jump at the general secondary school admission threshold for both skill measures.

The main results are collected in Tables 4, 5 and 6. First, in Table 4 we estimate the effect of secondary schooling on aggregate measures of cognitive and non-cognitive skills. According to the results in Table 4 completing secondary school has no significant causal effect on either cognitive or non-cognitive skills. The estimates are, not only insignificantly different from zero, but also small in magnitude. The reduced form estimates are relatively precise so that effects exceeding .13 both in cognitive skills and in non-cognitive skills fall outside the 95% confidence interval. Comparing these effects to the raw differences in skills across school type in Table 2 reveals that the differences across school type are mainly due to selection rather than the effects of different school types on skills. Causal effect of education on skills represents a negligible fraction of the observed skill differences across the schooling levels.

Table 5 presents the results related to individual test sections. Given that we found no effects on the aggregate-level skill measures it is not so surprising that we find no effects on the sub-test scores either. Also some cognitive skill measures, particularly the visuospatial test are related to fluid intelligence i.e. the ability to reason and think flexibly rather than crystalized intelligence i.e. accumulation of knowledge, facts, and skills that are acquired throughout life. Finding no effect on visuospatial test scores is consistent with previous results according to which fluid intelligence is independent of learning, experience, and education. (Eg. Cattell (1971), Almlund *et al.* (2011), Carlsson *et al.* (2015)).

Finding that type of secondary education has no effect on arithmetic or verbal abilities is perhaps more surprising. After all, there is much more training in math and much more reading and writing assignments in the general secondary school than in vocational schools. However, the Defence Forces Basic Skills Test measures rather basic arithmetic and verbal skills, not skills in differential calculus or essay writing. Note however, that these basic skills still have a strong correlation with later earnings and hence demonstrate value in the labor market.

In Table 6, we show the effects on the individual elements of the non-cognitive test. We find only one significant effect even for traits where the differences across school types are the largest again suggesting that these differences are mainly due to selection rather that effects of type of secondary schooling completed. The only effect that turns out to be statistically significant is a negative effect on masculinity.

As the cognitive skills test has three dimensions and non-cognitive test eight, multiple hypothesis testing may generate false positives. Our main approach to deal with this involves aggregating these 11 test scores to two dimensions which alleviates the problem. We also calculate q-values (Anderson, 2008) to control for false discovery rates. The effect on masuculity remains borderline significant after accounting for multiple hypothesis testing (q=0.06).

In the appendix, we test the robustness of our results in a number of ways. In Table A3, we use test scores anchored to earnings at ages 35–39 as the outcome variables. The anchoring procedure weights the test scores differently than factor analysis which could impact our findings. However, the estimates in Table A3 correspond to our main results and leave our conclusions unaltered. Next, we test the sensitivity of our main results to different bandwidth choices. Table A4 uses optimal bandwidths for each of our main outcomes. These estimates closely resemble our main results. Fig A5 reports the main results using bandwidths between .1 and 1 GPA units. The results show that our estimates are not sensitive to the choice of bandwidth as long as the bandwidth does not fall below .3. Finally, in Table A5, we perform a donut-RDD, where the marginal applicant is excluded, and add control variables for parents' education and earnings. Neither of these robustness checks significantly affect our result.

6 Conclusion

Admission to general versus vocational education after compulsory comprehensive school at age 16 leads to very different school environment for the following three years. General education is academically oriented and prepares students for higher education while vocational education focuses on practical occupation-specific skills. Also peer groups are different - students who end up in general education have more "higher quality" peers whether peer quality is measured by average school grades, test scores or parents' education.

According to the results in this paper, these differences in school environment have little effect on basic skills measured in the military tests at age 19 or 20. Despite large differences in the test scores between men with different educational backgrounds, we find no causal effects of education on cognitive or non-cognitive skills using a regression discontinuity design created by a centralized application system in Finnish secondary education. Thus, the differences in skills between the general and vocational tracks arise from selection rather than as a causal effect of schooling.

These results imply that important cognitive and non-cognitive skills are set at relatively young age and are not much affected by schooling after age 16, or that both types of secondary education tracks effect these skills in similar fashion. Given the large differences in the curricula between the education tracks this can be seen surprising. The more pessimistic interpretation of the results suggests that efforts to identify the effects of schooling on key cognitive and non-cognitive skills should focus on younger children.

Notes

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Tables

Table 1: Predictive power of test scores for log average earnings at ages 35 - 39

	(1)	(2)	(3)
Cognitive:			
Visuospatial	0.068***		0.064***
	(0.004)		(0.004)
Verbal	0.058***		0.043***
	(0.004)		(0.004)
Arithmetic	0.125***		0.105***
	(0.004)		(0.005)
Non-cognitive:			
Leadership motivation		-0.000	-0.012**
		(0.006)	(0.006)
Activity-energy		-0.013***	0.012***
		(0.005)	(0.005)
Achievement striving		0.095***	0.044***
		(0.004)	(0.004)
Self-confidence		0.112***	0.046***
		(0.005)	(0.005)
Deliberation		0.034***	0.047***
		(0.004)	(0.004)
Sociability		0.012**	0.044***
		(0.005)	(0.005)
Dutifulness		0.014***	-0.009**
		(0.004)	(0.005)
Masculinity		0.017***	0.015***
		(0.003)	(0.003)
N	137 495	146 685	136 387
R^2	0.039	0.031	0.051

Note: Test scores are standardized to have mean 0 and standard deviation 1. We use data on birth cohorts 1974-1979. All columns include birth cohort fixed effects. The dependent variable is log average annual earnings at ages 35-39 measured in 2018 euros. Robust standard errors are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Means of outcome and background variables by completed education.

	General	Vocational	No secondary
GPA (scale 4 to 10)	8.34	6.69	6.45
Average earnings at 35-39	46 000	33 600	26 300
Mother has at least secondary education	0.81	0.64	0.62
Father has at least secondary education	0.78	0.57	0.55
Parental income	320 200	233 200	230 200
Cognitive test score	0.69	-0.42	-0.56
Non-cognitive test score	0.36	-0.22	-0.30
Visuospatial	0.46	-0.29	-0.43
Verbal	0.63	-0.42	-0.52
Arithmetic	0.62	-0.40	-0.54
Leadership motivation	0.33	-0.25	-0.16
Activity energy	0.14	-0.02	-0.14
Achievement striving	0.39	-0.22	-0.35
Self-confidence	0.30	-0.11	-0.31
Deliberation	0.25	-0.05	-0.40
Sociability	0.19	-0.12	-0.07
Dutifulness	0.39	-0.19	-0.38
Masculinity	-0.15	0.20	0.06
N	59 394	59 572	24 468

Note: Test scores are standardized to mean 0 and standard deviation 1. Earnings and income are measured in 2018 euros. Parental income is the sum of the mother's and father's annual taxable incomes in 1991 to 1995.

Table 3: Effects of the admission threshold on pre-determined variables, peer characteristics and subsequent outcomes

Pre-determined variables		
Urban	0.004	(0.015)
Semiurban	-0.009	(0.011)
Rural	0.005	(0.013)
Mother's earnings	11	(3 300)
Mother has a secondary degree	0.039	(0.025)
Father's earnings	9 200*	(5 200)
Father has a secondary degree	0.014	(0.026)
Predicted cognitive test score	0.009	(0.006)
Predicted non-cognitive test score	0.009	(0.006)
Test taking		
Attended military†	0.018	(0.014)
Age at non-cognitive test	0.018	(0.032)
Age at cognitive test	0.040	(0.044)
Peer characteristics		
GPA (scale 4 to 10)	0.818***	(0.058)
Share of women	0.149***	(0.017)
Cognitive test score	0.433**	(0.034)
Non-cognitive test score	0.204**	(0.021)
Mother's earnings	9 600***	(1 200)
Mother has a secondary degree	0.071***	(0.009)
Father's earnings	18 200***	(3 100)
Father has a secondary degree	0.083***	(0.010)
Subsequent outcomes		
General secondary degree	0.179***	(0.026)
Vocational secondary degree	-0.219***	(0.027)
Secondary degree	-0.014	(0.024)
Tertiary degree	0.046*	(0.027)
Average annual earnings at ages 16-19	-10	(100)
Average annual earnings at ages 20-24	-1 000**	(400)
Average annual earnings at ages 25-29	-1 200	(800)
Average annual earnings at ages 30-34	200	(1 000)
Average annual earnings at ages 35-39	13	(1 300)
White collar job	0.011	(0.030)
Blue collar job	0.002	(0.025)

Note: Each entry in the table is an estimate from a local linear regression using triangular kernel weights and a bandwidth of .5 GPA units. Standard errors clustered by cutoff are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Earnings and income are measured in 2018 euros. Mother's and father's earnings are the sum of annual taxable incomes in 1991 to 1995. All regressions include fixed effects for each cutoff, interactions between each cutoff and the running variable, birth year fixed effects, and the first and second polynomials of age at test measured in days. We include age at test as a control to maintain the same specification as in our main estimates. † We do not include the age at test as a control in the regression for attending military, since this information is only available for those individuals that attended military and took the test.

Table 4: RDD estimates of the effect of general secondary education on the test scores

	Non-cognitive	Cognitive
Reduced form:	0.022	0.022
	(0.055)	(0.040)
Admission to general school:		
First stage:	0.645***	0.643***
	(0.023)	(0.023)
LATE:	0.034	0.034
	(0.086)	(0.062)
Completed general degree:		
First stage:	0.187***	0.182***
	(0.027)	(0.027)
LATE:	0.117	0.119
	(0.296)	(0.220)
N	8 322	8 322

Note: Each entry in the table is an estimate from a local linear regression using triangular kernel weights and a bandwidth of .5 GPA units. Test scores are standardized to mean 0 and standard deviation 1. All regressions include fixed effects for each cutoff, interactions between each cutoff and the running variable, birth year fixed effects, the first and second polynomials of age at test measured in days, and a dummy indicating if the individual took the non-cognitive test at the draft. Standard errors clustered by cutoff are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: RDD estimates of the effect of general secondary education on cognitive skills

	Visuospatial	Verbal	Arithmetic
Reduced form:	0.009	0.029	0.009
	(0.048)	(0.043)	(0.046)
Admission to general school:			
First stage:	0.638***	0.638***	0.638***
	(0.022)	(0.022)	(0.022)
LATE:	0.014	0.046	0.014
	(0.076)	(0.068)	(0.071)
Completed general degree:			
First stage:	0.180***	0.180***	0.180***
	(0.027)	(0.027)	(0.027)
LATE:	0.044	0.159	0.049
	(0.268)	(0.242)	(0.254)
N	8 375	8 375	8 375

Note: Each entry in the table is an estimate from a local linear regression using triangular kernel weights and a bandwidth of .5 GPA units. Each outcome variable is standardized to mean 0 and standard deviation 1. All regressions include fixed effects for each cutoff, interactions between each cutoff and the running variable, birth year fixed effects, the first and second polynomials of age at test measured in days, and a dummy indicating if the individual took the non-cognitive test at the draft. Standard errors clustered by cutoff are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: RDD estimates of the effect of general secondary education on personality traits

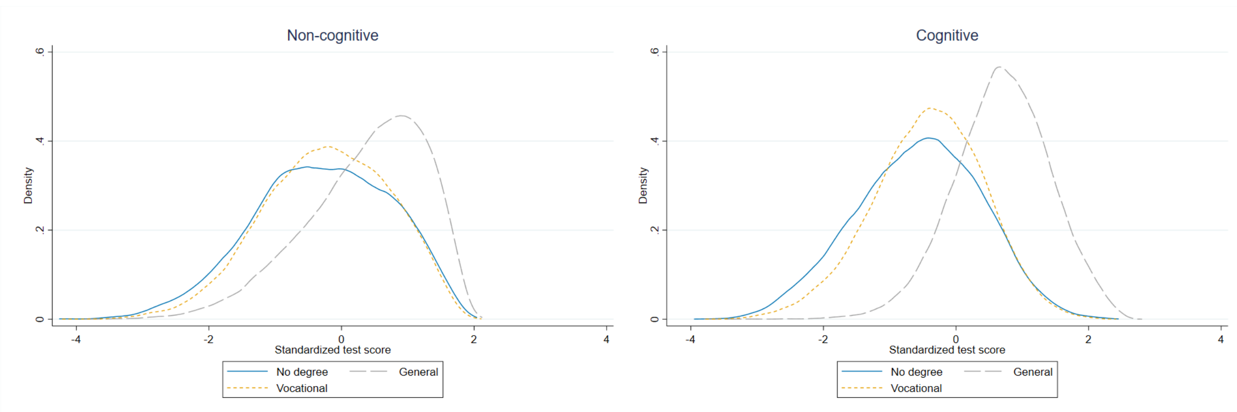
	Leadership motivation	Activity-energy	Achievement striving	Self-confidence
Reduced form:	0.057	-0.005	0.030	-0.033
	(0.057)	(0.059)	(0.054)	(0.051)
Admission to general school:				
First stage:	0.643***	0.643***	0.643***	0.643***
	(0.022)	(0.022)	(0.022)	(0.022)
LATE:	0.089	-0.009	0.046	-0.051
	(0.089)	(0.092)	(0.084)	(0.079)
Completed general degree:				
First stage:	0.181***	0.181***	0.181***	0.181***
	(0.026)	(0.026)	(0.026)	(0.026)
LATE:	0.313	-0.030	0.161	-0.182
	(0.319)	(0.326)	(0.300)	(0.280)
N	8317	8317	8317	8317

	Deliberation	Sociability	Dutifulness	Masculinity
Reduced form:	0.039	-0.011	0.037	-0.134***
	(0.062)	(0.055)	(0.059)	(0.050)
Admission to general school:				
First stage:	0.643***	0.643***	0.643***	0.643***
	(0.022)	(0.022)	(0.022)	(0.022)
LATE:	0.061	-0.017	0.058	-0.209***
	(0.096)	(0.086)	(0.091)	(0.079)
Completed general degree:				
First stage:	0.181***	0.181***	0.181***	0.181***
	(0.026)	(0.026)	(0.026)	(0.026)
LATE:	0.215	-0.061	0.205	-0.741**
	(0.341)	(0.304)	(0.322)	(0.292)
N	8317	8317	8317	8317

Note: Each entry in the table is an estimate from a local linear regression using triangular kernel weights and a bandwidth of .5 GPA units. Each outcome variable is standardized to mean 0 and standard deviation 1. All regressions include fixed effects for each cutoff, interactions between each cutoff and the running variable, birth year fixed effects, the first and second polynomials of age at test measured in days, and a dummy indicating if the individual took the non-cognitive test at the draft. Standard errors clustered by cutoff are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

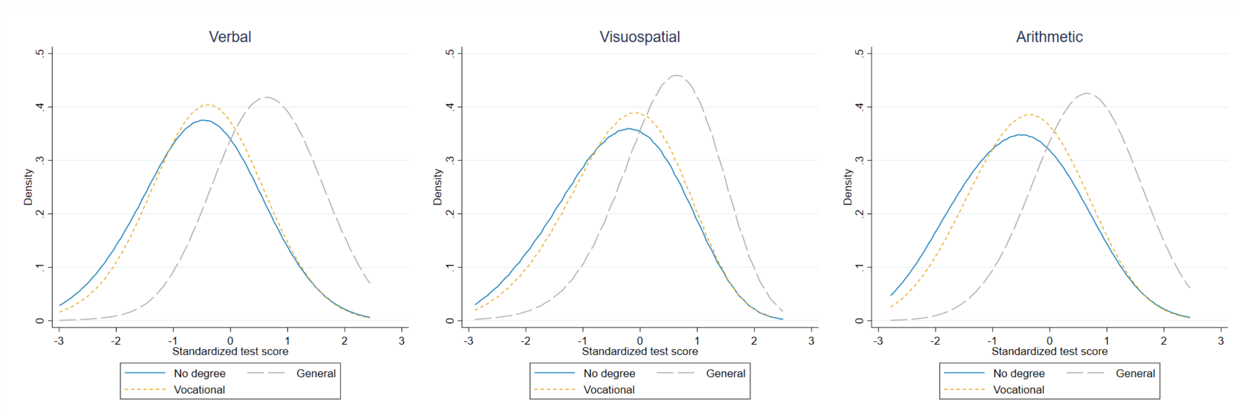
Figures

Figure 1: Distributions of test scores by education



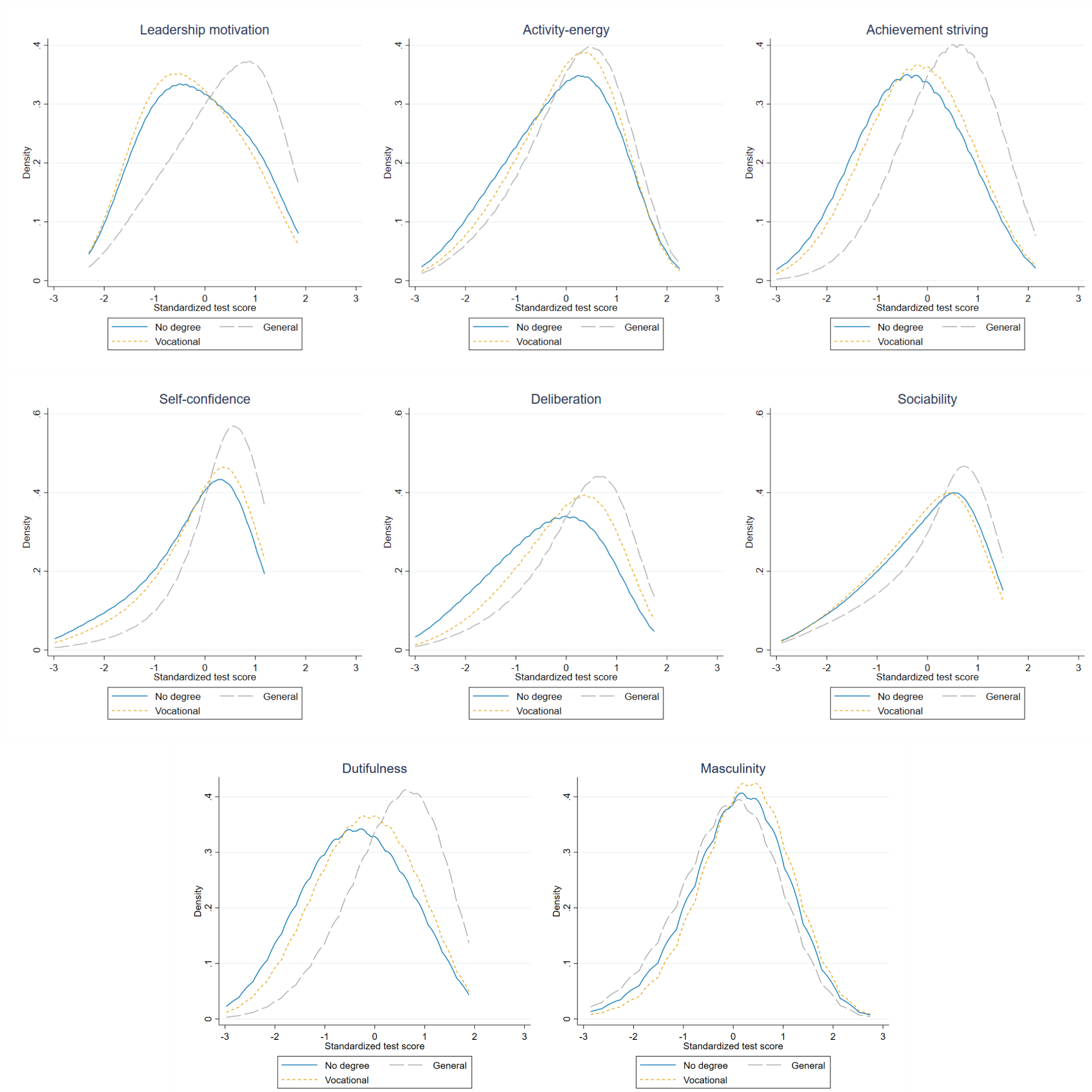
Note: Figure 1 shows the distributions of the standardized test scores by completed education at the time of taking the test. The sample includes men aged 18 to 22 at the end of the year in which they take the test.

Figure 2: Distributions of cognitive skills by education



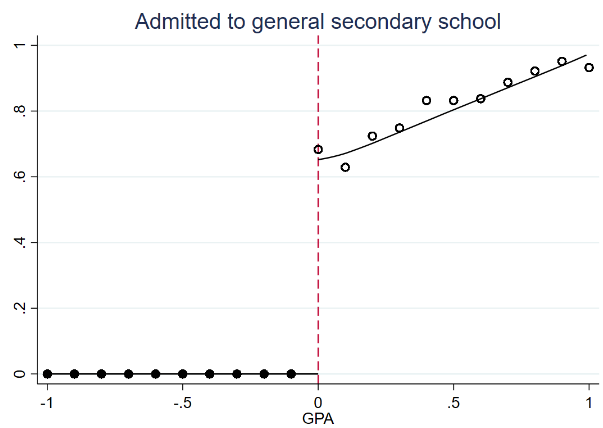
Note: Figure 2 shows the distributions of the cognitive skills by completed education at the time of taking the test. The sample includes men aged 18 to 22 at the end of the year in which they take the test.

Figure 3: Distributions of personality traits by education



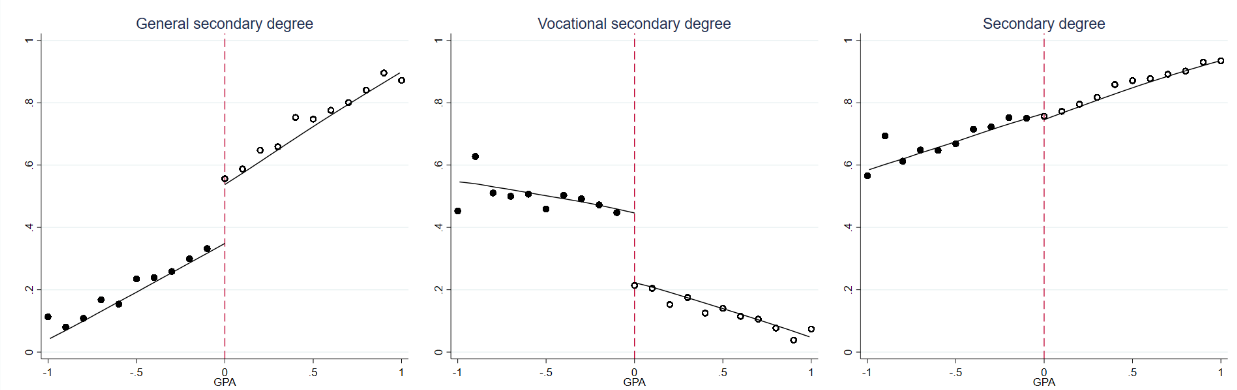
Note: Figure 3 shows the distributions of the personality traits by completed education at the time of taking the test. The sample includes men aged 18 to 22 at the end of the year in which they take the test.

Figure 4: Cutoff and admission into general secondary school



Note: Figure 4 shows the share of applicants admitted to general secondary education, plotted against the program-specific running variable. The dots depict sample means of the dependent variable for 0.1 GPA unit wide bins. The lines show local linear regressions weighted using an edge kernel and bandwidth 1.

Figure 5: Admission cutoffs into general secondary school and completed secondary degrees.



Note: Figure 5 shows the share of students completing a general secondary degree, a vocational secondary degree, or either of these by the test date, plotted against the program-specific running variable. The dots depict sample means of the dependent variable for 0.1 GPA unit wide bins. The lines show local linear regressions weighted using an edge kernel and bandwidth 1.

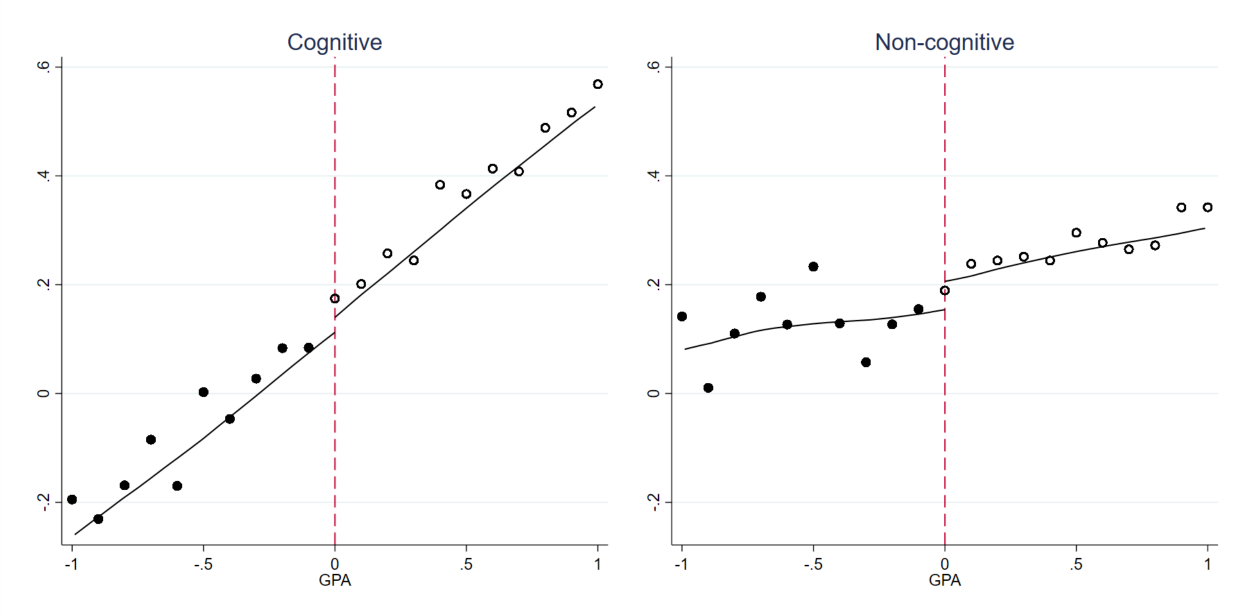
Appendix A. Tables and Figures

Distribution of raw scores

In the cognitive tests the raw scores are indicate number of correct answers. Number of questions in each cognitive test is 40. In the non-cognitive test the raw score indicates the number of statements that the respondent agrees with (or on case of reverse-coded statements disagrees with). The number of statements varies between 18 and 33 depending on personality trait. We have access to raw scores but not to the individual test items.

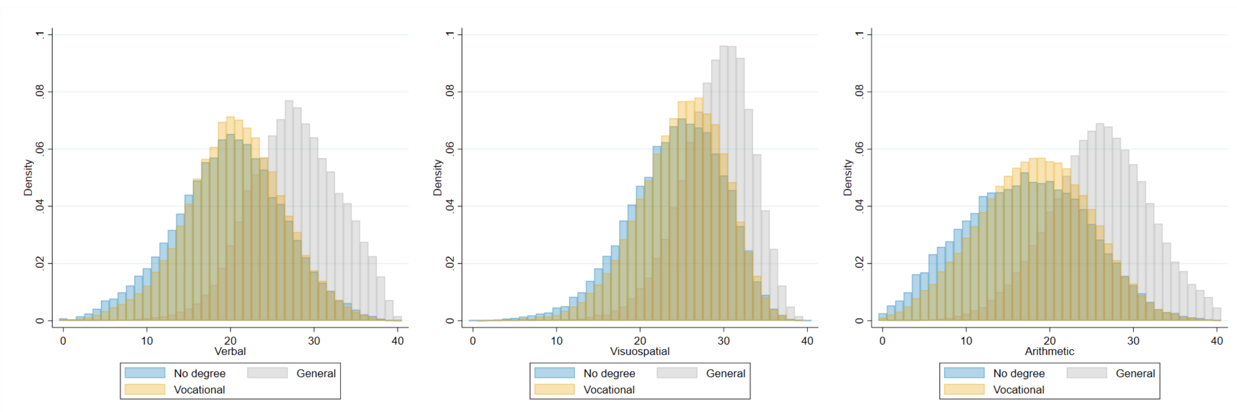
Figures A1 – A2 show the distributions of the raw test scores by completed education at the time of taking the test. The sample includes men aged 18 to 22 at the end of the year in which they take the test. Figure A1 plots test scores from the cognitive tests, while figure A2 plots the scores from the non-cognitive tests.

Figure 6: Test scores and admission cutoffs into general secondary education.



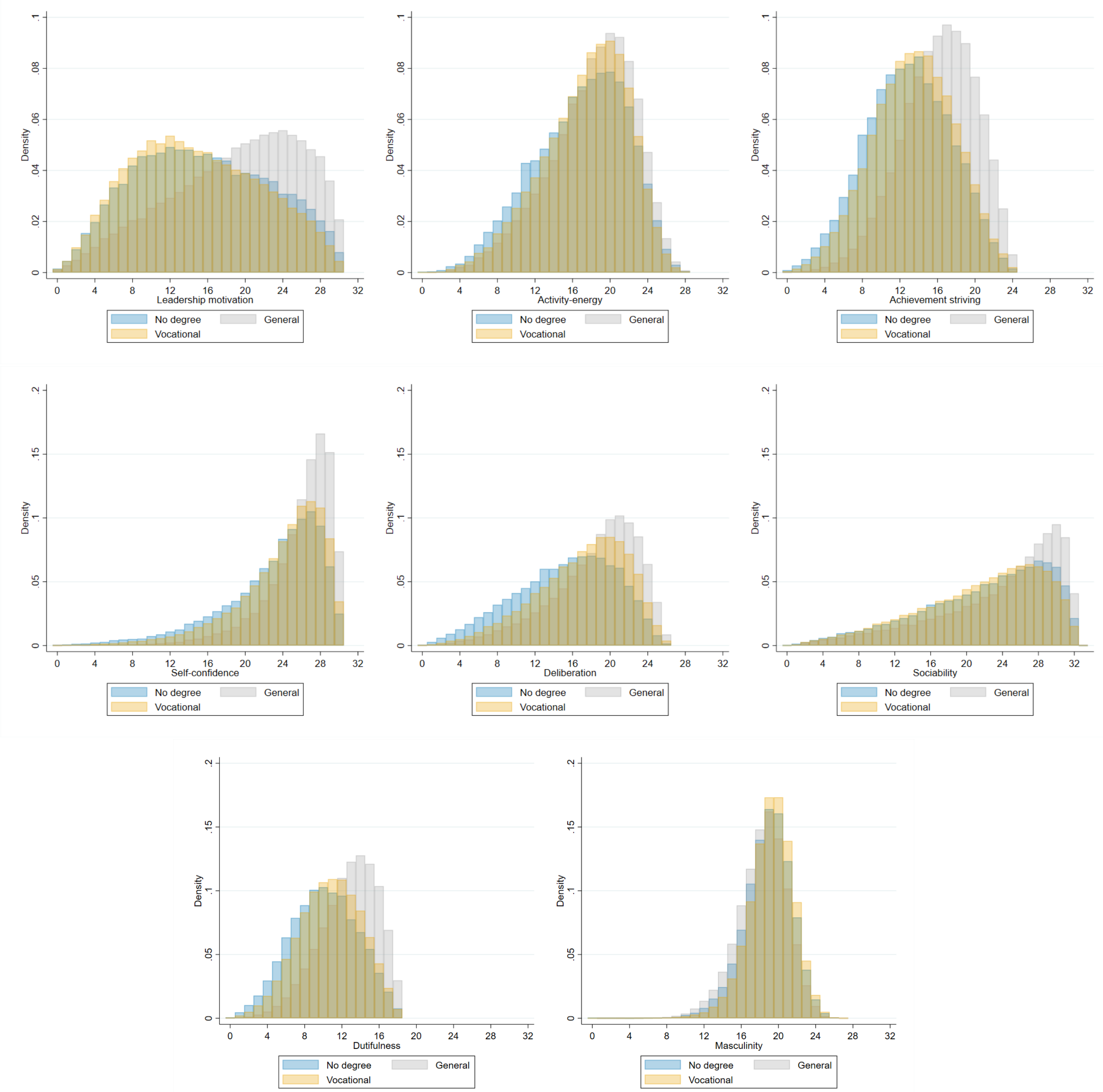
Note: Figure 6 plots the anchored test scores against the program-specific running variable. The dots depict sample means of the dependent variable for 0.1 GPA unit wide bins. The lines show local linear regressions weighted using an edge kernel and bandwidth 1.

Figure A1: Raw distributions of cognitive skills by education



Note: Figure A1 shows the raw distributions of the cognitive skills by completed education at the time of taking the test. The sample includes men aged 18 to 22 at the end of the year in which they take the test.

Figure A2: Raw distributions of personality traits by education



Note: Figure A2 shows the raw distributions of the personality traits by completed education at the time of taking the test. The sample includes men aged 18 to 22 at the end of the year in which they take the test.

Factor analysis

The army test score data contains 3 cognitive skill scores and 8 non-cognitive skill scores. Both the cognitive scores and the non-cognitive scores are strongly correlated within their domains but the correlations across cognitive and non-cognitive domains are modest. More detailed description of individual test items and test procedures is reported in the supplementary material for Jokela *et al.* (2017) that we follow in this section.

We use factor analysis to reduce the dimensionality of the test score data. Only two first eigenvalues exceed one, suggesting that a two-factor model would be a sufficient description of the data. The two first factors already explain most of the variability in the test scores when principal factor analysis is used.

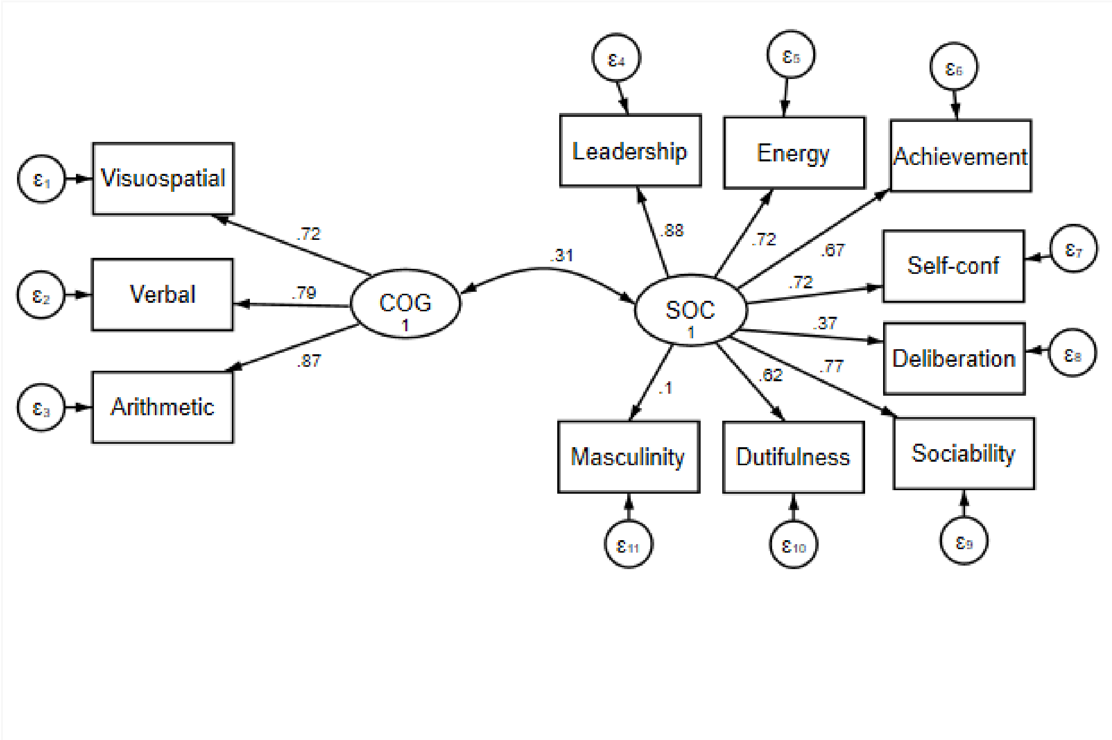
An examination of the factor loadings in exploratory factor analysis supports the conclusion based on eigenvalues. The cognitive and the non-cognitive test scores load on separate factors irrespective of whether orthogonal varimax rotation or obligue rotation that allows the factors to be correlated is used. Masculinity is only weakly related to other non-cognitive scores. It also has large uniqueness and small factor loading. We retain it mainly because it is part of the original army test battery. Results dropping this measure are not much different.

Table A1: Factor loadings

	Cognitive	Non-Cognitive	Uniqueness
Visuospatial	**0.719**	-0.029	0.495
Verbal	**0.769**	0.014	0.401
Arithmetic	**0.809**	0.007	0.343
Leadership motivation	0.030	**0.833**	0.290
Activity - Energy	-0.120	**0.765**	0.458
Achievement motivation	0.156	**0.615**	0.539
Self-confidence	0.060	**0.718**	0.455
Deliberation	0.016	**0.447**	0.795
Sociability	-0.104	**0.776**	0.437
Dutifulness	0.110	**0.637**	0.540
Masculinity	-0.134	0.169	0.968

Note: Factor loadings exceeding 0.3 are marked in **bold**

Figure A3: Factor structure in army test data



Note: In figure A3 ovals shapes indicate latent factors, rectangles observed scores, curved lines correlation between factors and straight lines factor loadings.

Based on the exploratory factor analysis we assume that there are two underlying unobserved latent factors, one related to the cognitive and one related to the noncognitive skills. We allow for a possible correlation between these latent skills but constrain the cross-loadings to zero so that each measure is associated with only one latent factor. We scale the latent variables by constraining their variances to be equal to one. Graph A3 describes the structure of the model.

We then estimate the factor loadings (effect of latent variables on observed test scores) and the error variances (variance of observed test scores not explained by the latent variables). The two-factor model provides a reasonably good fit to the data (CFI=0.818, RMSEA=0.145). Low correlation between the cognitive and non-cognitive latent factors (r=0.31) also indicates that there are two independent latent factors. Factor scores are estimated with regression scoring after fitting the model

OLS estimates

Table A2 presents OLS estimates of the effects of completing the general secondary school on the test scores. In particular, we study how the estimated effects are affected by restricting the sample and accounting for selection on observable characteristics. The effects are estimated separately using either the full sample or the RDD sample as described in section 3.3 with and without control variables.

In the first panel, we use the full sample. The estimated effects of completing a general degree on the test scores without control variables are large and correspond to the differences in average test scores presented in Table 2. According to these estimates, completing a general degree has an effect of 61 % of a standard deviation on non-cognitive skills and 111 % of a standard deviation on cognitive skills. Adding control variables for GPA, age at test, and birth year reduces the size of the estimated effects significantly.

In the second panel, we restrict the estimation sample as we do for our RDD design. The effects with and without controls are now smaller than the corresponding estimates in the first panel. By using the RDD sample, we exclude those individuals who only applied to vocational school or dropped out at the end of compulsory school. These individuals score lower in the skills tests which contributes to the smaller estimates than with the full sample. However, even after adding control variables, especially the estimated effects on cognitive skills are still large compared to our RDD estimates in Table 4.

Table A2: OLS estimates of the effects of completing general secondary education on test scores.

	(1) Non-cognitive	(2) Cognitive	(3) Non-cognitive	(4) Cognitive
Full sample:				
Completed general degree	0.606***	1.148***	0.292***	0.465***
	(0.006)	(0.004)	(0.009)	(0.007)
N	143 512	143 512	118 427	118 427
Controls	NO	NO	YES	YES
RDD sample:				
Completed general degree	0.245***	0.650***	0.115***	0.226***
	(0.011)	(0.009)	(0.014)	(0.011)
N	41 164	41 164	41 164	41 164
Controls	NO	NO	YES	YES

Note: Full sample includes men aged 18 to 22 at the end of the year in which they take the test from birth cohorts 1974-1979. RDD sample refers to the estimation sample used in our RDD estimates (see section 3.3). Control variables include dummies for .5 wide GPA intervals, age at test, age at test squared, and birth year dummies. Robust standard errors are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Regression results with test scores anchored to later earnings

As an alternative dimension reduction to factor scores used in main analysis, we follow the example in Cunha *et al.* (2010) and anchor the test scores to later earnings data. In addition to reducing dimensionality, the procedure also generates a meaningful scale for the outcome variables.

In this approach we regress earnings at age 35 - 39 on the raw test scores and use predicted values from this regression as skill measures. Note that these predicted values can also be calculated for the men (12%) with zero earnings or no valid earnings information as long as they have non-missing data on the test scores. In order to generate a common scale that is comparable across different levels of education, we need to estimate a pooled regression model for all schooling levels. Naturally it is possible that some skills are more relevant for those with academic education and other skills for those with vocational education and that skills affect the choice of education as in the Roy model. (Roy, 1951)

The results with anchored test scores are collected in table A3. In the first column the predicted variables are generated from a regression of earnings on non-cognites skills, in the second column from a regression on cognitive skills an in the third column from a regression explaining earnings by both cognitive and non-cognitive skills.

According to the results in Table A3 completing upper secondary school has no significant causal effect on either cognitive or non-cognitive skills. The estimates are, not only insignificantly different from zero, but also small in magnitude. The estimates are relatively precise so that effects exceeding 10% in cognitive skills and estimates exceeding 6% in non-cognitive skills fall outside the confidence interval.

Table A3: RDD estimates of the effect of general secondary education on the anchored test scores

	Non-cognitive	Cognitive	All
Reduced form:	-0.002	0.004	0.002
	(0.007)	(0.008)	(0.010)
Admission to general school:			
First stage:	0.643***	0.643***	0.643***
	(0.022)	(0.022)	(0.022)
LATE:	-0.003	0.006	0.003
	(0.011)	(0.012)	(0.016)
Completed general degree:			
First stage:	0.181***	0.181***	0.181***
	(0.027)	(0.027)	(0.027)
LATE:	-0.011	0.020	0.009
	(0.038)	(0.043)	(0.055)
N	8 317	8 317	8 317

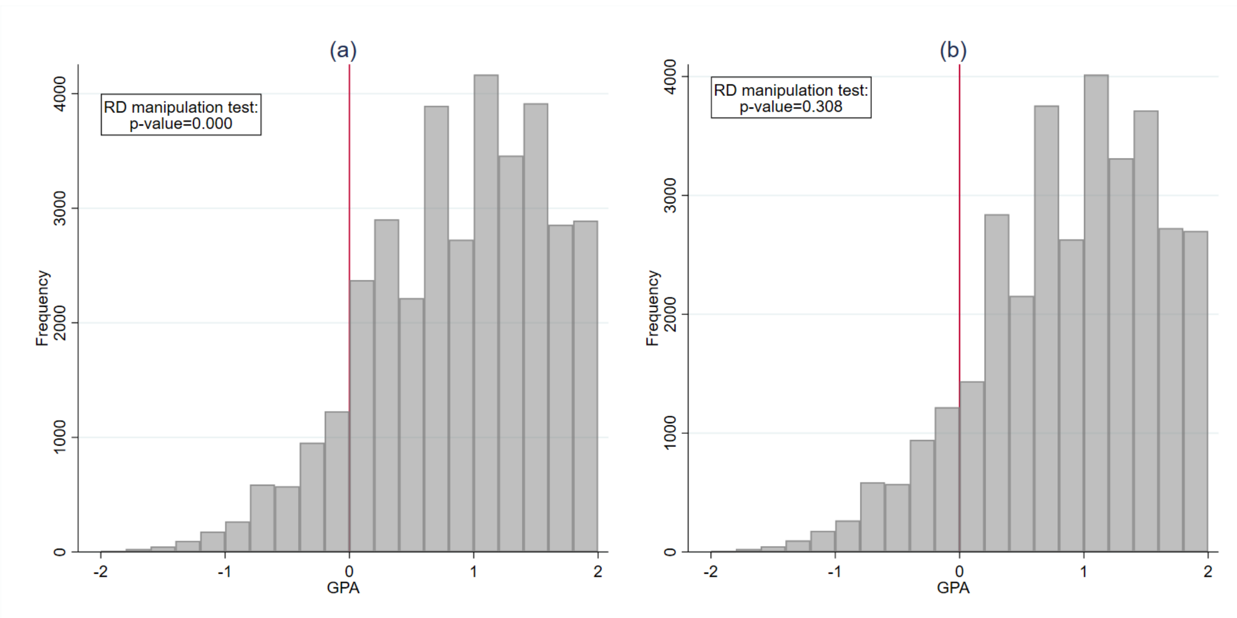
Note: Each entry in the table is an estimate from a local linear regression using triangular kernel weights and a bandwidth of .5 GPA units. All regressions include fixed effects for each cutoff, interactions between each cutoff and the running variable, birth year fixed effects, the first and second polynomials of age at test measured in days, and a dummy indicating if the individual took the non-cognitive test at the draft. Standard errors clustered by cutoff are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Frequencies around the cutoff

Figure A4 reports GPA histograms to check for manipulation of the running variable around the cutoff. The left-hand panel shows the GPA distribution using our main estimation sample. Since our cutoff is defined by the last admitted applicant to each program, there is a noticeable spike exactly at the cutoff. Consequently, the main estimation sample fails the density test proposed by (Cattaneo *et al.*, 2020).

However, in the right-hand panel we exclude the marginal applicant and the corresponding histogram confirms that this bunching is indeed mechanical in nature. The spike detected in the left-hand panel largely disappears when the marginal applicant is dropped and this pattern is also confirmed by the density test.

Figure A4: Density across the cutoff.



Note: Figure A4 reports the number of applicants within each .2 GPA unit wide bins. Panel (a) shows a density graph using the main estimation sample. Panel (b) shows a donut density graph where the marginal applicants used to define the cutoffs excluded. We also report p-values from the density test proposed by Cattaneo *et al.* (2020).

RDD bandwidth

In Table A4, we estimate the effect of general secondary education on the test scores with optimal bandwidths selected using the selection procedure in (Calonico *et al.*, 2014). The bandwidths are selected separately below and above the cutoff. As in Table 4, the estimates are close to zero and insignificant, leaving our conclusions unaltered.

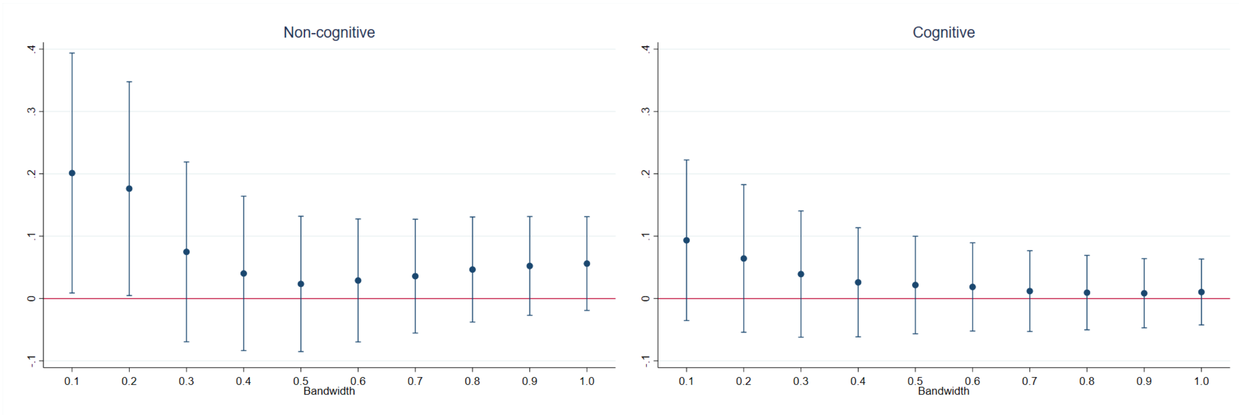
Table A4: RDD estimates of the effect of completing general secondary education on test scores using optimal bandwidths

	Non-cognitive	Cognitive
Reduced form	0.026	0.001
	(0.046)	(0.032)
Admission to general school:		
First stage:	0.594***	0.591***
	(0.021)	(0.020)
LATE:	0.043	0.001
	(0.077)	(0.054)
Completed general degree:		
First stage	0.171***	0.167***
	(0.023)	(0.021)
LATE	0.151	0.003
	(0.267)	(0.193)
N	19 334	17 977
Optimal bw below/above	.37/1.16	.50/1.02

Note: Each entry in the table is an estimate from a local linear regression using triangular kernel weights and the optimal bandwidths selected separately below and above the cutoff using the selection procedure in (Calonico *et al.*, 2014). All regressions include fixed effects for each cutoff, interactions between each cutoff and the running variable, birth year fixed effects, the first and second polynomials of age at test measured in days, and a dummy indicating if the individual took the non-cognitive test at the draft. Standard errors clustered by cutoff are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In Figure A5, we examine the robustness of our main estimates to different bandwidths. Figure A5 reports the reduced form estimates for a range of bandwidths from .1 to 1 GPA units on both sides of the cutoff along with the corresponding 95 percent confidence intervals. In general, the estimates resemble our main results in that they are close to zero and statis-

Figure A5: Robustness to alternate bandwidths.



Note: Figure A5 plots the RDD estimates of crossing the admission threshold on the standardized test scores from local linear regressions using triangular kernel weights. We present estimates for bandwidths ranging from .1 to 1 GPA units on both sides of the cutoff. All regressions include fixed effects for each cutoff, interactions between each cutoff and the running variable, birth year fixed effects, the first and second polynomials of age at test measured in days, and a dummy indicating if the individual took the non-cognitive test at the draft. For each point estimate, we also present the 95 percent confidence intervals. Standard errors are clustered by cutoff.

tically insignificant, except for the estimates with the smallest bandwidths of .1 and .2 for the non-cognitive test scores. However, the estimates quickly become smaller in magnitude and statistically insignificant when moving to larger bandwidths.

Additional robustness checks

In Table A5 we perform two additional robustness checks on the main results. First, since the admission cutoffs are defined by the last accepted student into a program, we want to ensure that our estimates are not biased by possible endogeneity arising from this definition. To this end, we use a donut-RDD strategy where we drop the applicants who determine the cutoffs in our sample. The reduced form estimates using this strategy are presented in the first panel of Table A5. The estimates remain close to zero and insignificant.

Second, since we observed a discontinuity in father's earnings at the cutoff, we test whether our estimates are sensitive to the inclusion of controls for parental background. The second panel of Table A5 shows estimates from a model with controls for both parents' earnings and whether they had secondary education. The inclusion of these controls does not significantly affect our estimates.

Table A5: Robustness checks

	Non-cognitive	Cognitive
Donut:		
	-0.054	-0.019
	(0.084)	(0.056)
N	7 295	7 295
Parental controls:		
	-0.013	0.018
	(0.058)	(0.042)
N	7 856	7 856

Note: Each entry in the table is an estimate from a local linear regression using triangular kernel weights and a bandwidth of .5 GPA units. All regressions include fixed effects for each cutoff, interactions between each cutoff and the running variable, birth year fixed effects, the first and second polynomials of age at test measured in days, and a dummy indicating if the individual took the non-cognitive test at the draft. Standard errors clustered by cutoff are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.