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DISCUSSION PAPER SERIES

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# ABSTRACT

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

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 covers the vast majority of Finnish men and is a strong predictor of later labor market success. We find that large differences in 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.

**JEL Classification:** J24, I21

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

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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 especially non-cognitive skills has grown over time.[1]

Despite this consensus on the growing importance of skills, there is relatively little empirical research on the factors that affect the formation of these skills. In particular, even though it is well-known that both cognitive and non-cognitive skills are highly correlated with educational attainment, there is little evidence on the causal effect of schooling on skills. The question of the effect of schooling on skills is especially relevant in the case of secondary education. In most school systems, this is the first important choice about educational content that adolescents make and is often presented as a trade-off between job-specific skills taught in vocational secondary education and more general skills taught in academically orientated general secondary schools.

This paper studies the effect of the type of secondary education (general vs vocational) on both cognitive and non-cognitive skills of young Finnish men. We measure these skills with an extensive psychological test battery conducted during mandatory military service that provides us with data on skills of several almost full male cohorts. To identify the effect of general versus vocational secondary education, we use a regression discontinuity design created by the centralized admission mechanism in Finland. In this system, the fact that the oversubscribed schools admit student based on the compulsory school GPA creates admission thresholds around which we can compare the admitted and rejected applicants.

Most convincing evidence on the factors affecting the formation of skills comes from randomized experiments that analyze programmes such as the Perry Preschool Project or the Carolina Abecedarian Project. These studies show that early educational interventions have

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

positive short-term effects on cognitive skills and also succeed in improving non-cognitive skills later in life.[2] However, the interventions studied in these papers often target disadvantaged groups in very particular contexts. Moreover, they usually mix education with other support measures such as home visits and nutritional aid. Therefore it is not clear how informative this evidence is on the capacity of the formal school system to boost cognitive and non-cognitive skills.

The research on the effect of the formal school system on skills has mainly concentrated on the effect of access to formal pre-school programmes (Cascio and Schanzenbach (2013), Cornelissen et al. (2018), Gupta and Simonsen (2010), and Fort et al. (2020)) as well as the effect of age at school entry (Bedard and Dhuey (2006), Crawford et al. (2007), Datar (2006), and Cornelissen and Dustmann (2019)). However, the evidence on the effect of the content of primary and, especially, secondary education on skills is much scarcer. The few existing studies exploit large-scale comprehensive school reforms to estimate either the intention-to-treat effect of the reforms on skills, as in Pekkala Kerr et al. (2013), or use the reforms as instruments for years of schooling as in Brinch and Galloway (2012). Although these studies find positive effects on some measures of cognitive skills, they still essentially estimate reform effects that mix effects of various changes in schooling that these reforms entailed.

We argue that the effect of the type of secondary schooling on skills is a crucial question for education policy. Whether to train adolescents with general skills or with skills that are relevant for specific occupations is one the key questions that governments around the world struggle with when trying to respond to challenges imposed by rapid technological change (Hanushek et al., 2017). However, for this trade-off to be relevant, the general track of the secondary school needs to be successful in shaping general skills. We believe that the evidence on the effect of the general track on cognitive and non-cognitive skills can inform the debate on the relative strengths of general vs vocational secondary education.

To the best of our knowledge, the previous literature has not successfully examined this

[2] Cunha et al. (2006), Currie and Almond (2011), and Almlund et al. (2011) are useful surveys of this literature.

question. Perhaps the closest study to our work in the previous literature is the Swedish study by Carlsson et al. (2015) who study the effect of the length of general secondary education on cognitive skills and find substantial positive effects. However, as this paper only exploits variation in the length of schooling within the general track, it does not really provide evidence on the effect of general vs vocational education on skills.

We measure cognitive and non-cognitive skills using test score data from the Finnish Defense Forces. 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. Access to military test data therefore provides us with measures of both cognitive and non-cognitive skills for almost entire cohorts of young men. We will 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.

Finnish men enter military service typically at age 19 or 20. At this age there are already important differences in completed schooling between individuals. Almost no one has a college degree when entering military service, but by age 19 academically oriented men have usually already completed their secondary schooling and taken the matriculation examination that universities use as an admission criteria. Others have participated in vocational secondary education for two or three years or dropped out of school at the end of comprehensive school at age 16.

Our data show that there are large differences in cognitive and non-cognitive skills between men that have obtained general and vocational secondary school degrees at the time they enter military service. Average cognitive skills of general secondary school graduates are .9 standard deviations higher than average cognitive skills of vocational school graduates. The same difference in non-cognitive skills is .3 standard deviations.

Naturally the differences in average skills across persons that differ in their education do not imply that the schooling has an impact on these skills or that these skills have been fostered at secondary school. The skill differences could equally well reflect selection to the different levels education or selection to different schooling tracks. In this paper, we use admission cutoffs as an exogenous source of variation to remove selection bias and to identify causal effects of education on skills.

In the Finnish school system, compulsory comprehensive school ends at age 16 after which most students apply to the secondary schools. Admission is based on grade point average at the end of comprehensive school. In the oversubscribed schools, this system creates discontinuous thresholds with very similar applicants on both sides of the thresholds. We use these thresholds in a regression discontinuity design to study the effect of admission to the general secondary school on the cognitive and non-cognitive test scores in the Finnish Defence Forces Basic Skills Test.

The content of education varies considerably between general and vocational schools. The 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. Often vocational training also takes place at the workplaces rather than in the classroom. This variation in content is in stark contrast with the compulsory comprehensive school which leaves very little room for choice and aims at providing basic skills for the full cohort.

Our data also show that the peer groups that the students study with differ vary considerably across general and vocational tracks. General secondary school students have much higher grade point average from the comprehensive school than vocational track students and have, on average, parents with higher education and earnings. Also gender composition is different. The majority of the general secondary school students are girls while the vocational programs are more popular among boys. Vocational programs are also strongly segregated by gender so that an average boy attending a vocational program will have mostly male classmates.

As a consequence, 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 depending on their school assignment at age 16. The main question in this paper is how these schooling years at ages between 16 and 19 affect cognitive and non-cognitive skills of young men. Our results indicate that secondary school type 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 achievement motivation and self-confidence. Interestingly, we observe that admission to general secondary school, or perhaps exposure to female classmates, decreases measures of masculinity.

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 present the main results. Section 5 concludes the paper.

# 2 Institutional background

## 2.1 Finnish secondary schooling system

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

There are two main options at the secondary level. General secondary schools (lukio) offer an ambitious academic program that prepares students for tertiary education either in traditional universities or in 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 the students can study at their own pace and many graduate only after four years. General secondary school students study Finnish, math, natural sciences, humanities and on average 2.5 foreign languages. The general secondary school ends in matriculation examination that provides general eligibility to university-level studies but no professional qualifications.

The main alternative is vocational education that provides practical training and vocational competences in specific occupations. The largest fields are manufacturing and construction (26%); business and administration (21%), health and welfare (19%) and services (19%). The students also take some general courses but over 80 % of training is concentrated on practical skills. A large share of training takes place at workplaces under supervision of a more experienced worker.

Currently 54% of those who finish comprehensive school continue in the general secondary school and 40% in vocational education. The remaining 6% either participate in the extra 10th grade of comprehensive school or quit school at age 16. General secondary school is more popular among girls. Only 43% of boys go to general secondary school while 54% of boys continue in vocational education after comprehensive school.

## 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 (FNBE). The process starts in February-March of the final 9th year of comprehensive school. The students can apply to up to five different post-compulsory programs (programs in different schools or different programs within schools).

Admission is based on program-specific admission scores. For most general secondary school program this score is solely based on the comprehensive school grade point average (GPA). Many vocational programs grant extra admission points for work experience or use aptitude tests in addition to grades.[3]

The students receive their final grades in May and therefore do not know their exact admission points or admission cutoffs at the time when they apply. As the cutoffs vary from year to year, students cannot either accurately predict whether they will be admitted into a

[3] In our data, we do not observe the points for these different admission criteria. Therefore, we focus on admission into the general track.

particular program, making strategic application behaviour difficult.

The supply of slots in each educational program is fixed and announced before the application process begins. Applicants are allocates to schools using a DA algorithm (Gale and 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 track or every unmatched candidate is rejected by every program listed in her application. At the end of this automated admission stage, in June of the final year of comprehensive school, applicants receive an offer with 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. This updating process affects roughly 10 percent of applicants in our period of study.

This paper focuses on applicants who are at the margin of being admitted into the general secondary schools. On average, the entry requirements to the general secondary schools are substantially higher than the entry requirements to vocational training so that the students who are not admitted to the general secondary schools are typically admitted to the vocational schools if they have listed a vocational alternative in their application.

The main educational options for those not accepted to any secondary education programs are the optional 10th grade of comprehensive school and preparatory vocational training. After this most students re-apply to secondary education in the following years. However, as failed applicants 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.

Currently 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 but it is possible to apply as a volunteer to service at age 18 of request for a postponement due to e.g. on-going education. There have been some changes in the draft system over time. Cohorts born in 1970 or earlier were drafted at age 19 and typically entered military service during the year they turned 20.

The draft also 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.

In the years that we examine, the duration of armed military service was either 8 or 11 months (those trained as officers had longest service times). Non-military service lasted for 12 months. With few exceptions detailed below, the tests that we use in this paper were taken during the military service. Hence, we have no test data on those in civil service nor on those exempt from service.

# 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 at the beginning of their military service with a battery of cognitive and non-cognitive skills tests. At the time of the test these conscripts are typically 19 or 20 years old. During the period covered in our data on average 70% of men performed military service and took the skill test battery. As we demonstrate later in Table 3, admission to general secondary school has no effect on the likelihood of entering military service.

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 very similar to the ability test used in Swedish military described in eg. Grönqvist et al. (2017) It has three forty-question sets that measure verbal and numerical skills and logical reasoning. In particular, 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. Also this test has several parts. We use data from the leadership inventory which contains eight measures of traits that the army psychologists judge to be important characteristics for the military leaders.[4] Each trait is measured with 20 to 30 statements with which the test-taker is asked to agree or to disagree. The individual test items are not published and the entire test is a military secret. However, the Defence Forces have released some sample statements for each trait.

The test battery is rather extensive. The cognitive test has 120 items and the leadership inventory part of the non-cognitive test 218. 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. The test is conducted at the military base in standardized conditions. Between 1995 and 2000 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 military reverted back to the practice of testing conscripts at the beginning of service. (Nyman, 2007)

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

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

higher in the military tests are more educated and earn more between ages 30-34. Jokela et al. (2017) also validate measures of the leadership inventory also against 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 of BIG5.

Psychological test scores have no natural scale. To make the magnitudes of the estimates easier to interpret we follow the example in Cunha et al. (2010) and anchor the test scores to later earnings data. This also reduces the dimensionality of the tests in a natural way and makes comparisons of the magnitude of differences in effect on different skills meaningful. We will describe the anchoring procedure in more detail after first introducing the other data sources.

### 3.2 Data on earnings and education

Our earnings data are based on tax records. The earnings definition that we use in this paper contains annual wage earnings excluding taxable benefits. Data is available from 1987 onward on the annual basis. Linking tax data across years as well as linking tax data to other data sources is relatively easy using person id's. For the main part of our analysis, we use average log annual real non-zero earnings at ages between 35 and 39. As shown by Böhlmark and Lindquist (2006) earnings at this age are highly correlated with lifetime earnings. Tax data has practically no measurement errors but taking an average over five years still reduces the effects of random fluctuations and avoids some issues with zero earnings during periods outside the labor force.

Education data comes from two main sources. Data on completed degrees are based of Statistics Finland Register of Degrees and Examinations. It covers all degrees completed in Finland and is based on direct reports from all degree-granting institutions. Data on applications and admissions to secondary education are based on records from Joint National Application Register maintained by National Board of Education. It contains all applicants to the secondary schools with information on their applications to different schools in preference ranking, final grades from the comprehensive school and admission decisions to all secondary school programs.

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

Information in different registers is linked together using person id numbers. All data files then are stored on Statistics Finland remote access system and are used in this study in an anonymous form.

## 3.3 Estimation sample

We restrict our estimation sample to include conscripts who were between 18 and 22 years old in the end of the year than they took the Basic Skills Test. This mainly omits those who postpone their service due to participation in college-level education and naturally those who are exempt from military service or enter civil service.

We also exclude 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 these from the sample has practically no effect on the key results.

The results from the full Basic Skills test are currently available from the year 1982 when 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 up to 2015, but Defence Forces have not released data on the new non-cognitive test that was adopted in 2000.

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

Tax records on annual earnings are available at the time of writing from 1989 until 2018.

As we measure earnings at ages from 35 to 39, access to earnings data does not restrict the range of cohorts available for the analysis.

To maximize the sample size while maintaining comparability we restrict data on cohorts who applied to secondary school in years from 1991 to 1995. As we study the effects of general secondary schools the sample is naturally also restricted to individuals who applied to the general secondary school. The men in final data were born between 1973 and 1979 and performed their military service between 1992 and 1999.

We also make the following restrictions to our estimation sample. First, we focus our analysis on first time applicants who are between 15 and 17 in age at the end of the year when applying to secondary school (average age is 16). Second, we exclude programmes 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 programmes that do not meet this requirement as well as applicants to these programmes. Our final estimation sample has 41,164 applicants in 1144 programme-year combinations.

### 3.4 Anchoring

We convert the test scores to an interpretable scale by anchoring the test scores to later earnings. In practice, we calculate the natural logarithm of 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.[5]

In Table 1, we report the results from these anchoring 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 tests but for easier interpretation we have normalized these scores to have standard deviation of one in this regression and use these normalized scores as explanatory variables in the anchoring regressions.

[5]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

Table 1: Anchoring test scores to log average earnings at ages 35 to 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. For the anchoring regressions, we use data on birth cohorts 1974-1979. All columns include birth cohort fixed effects. The dependent variable is the natural logarithm of average annual earnings at ages 35-39 measured in 2018 euros. Robust standard errors are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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 strong correlation with future earnings. In particular, measures related 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 in the log earnings regression. 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 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 earlier. (See eg. Borghans et al. (2008); Kautz et al. (2014); Jokela et al. (2017) ; Edin et al. (2022))

In this paper, the main focus is in the effect of schooling on skills. The estimates on the correlation between skills and earnings serve two main purposes. First, they verify that the test scores we use in this paper have external validity i.e. that the measured skills are relevant in the labor market. Second, they help to interpret the results by creating a meaningful scale for the test scores.[6]

Anchored test scores are simply predicted values from a regression model explaining earnings with the test scores. Note that these scores 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. Effectively anchoring simply weights the different sub-scores in a natural way and rescales the test scores so that the effects on skills are easier to interpret.

### 3.5 Descriptive statistics

Figure 1a plots the anchored 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 but make no other restrictions to data.

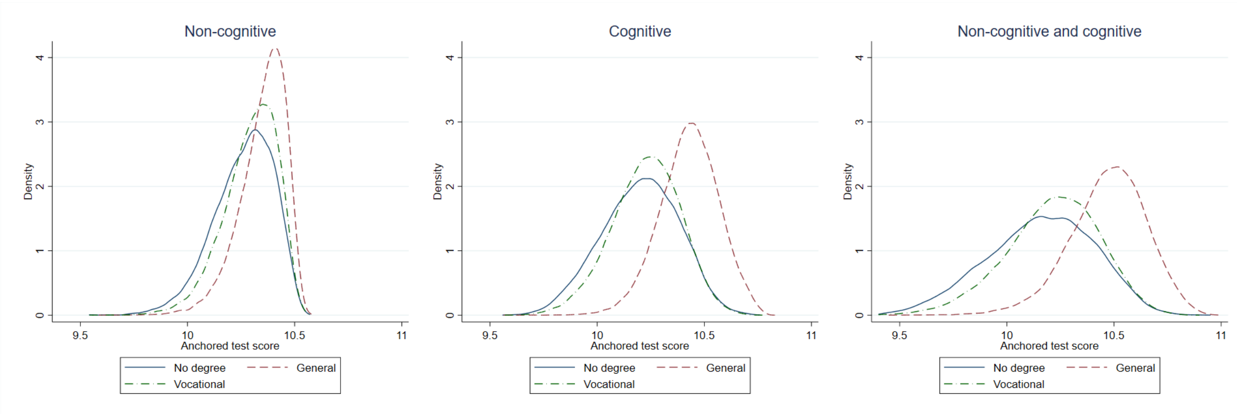
Figure 1 reveals large differences across men with different education at the test date. Apparently the difference in cognitive skills across men with different schooling levels is substantially larger than the difference in non-cognitive skills.

The men who have completed a general secondary education 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 difference between men with vocational education and men with no completed education by the time of entering the military service are rather similar. In what follows, we therefore mainly compare men with general secondary education to the rest of men.

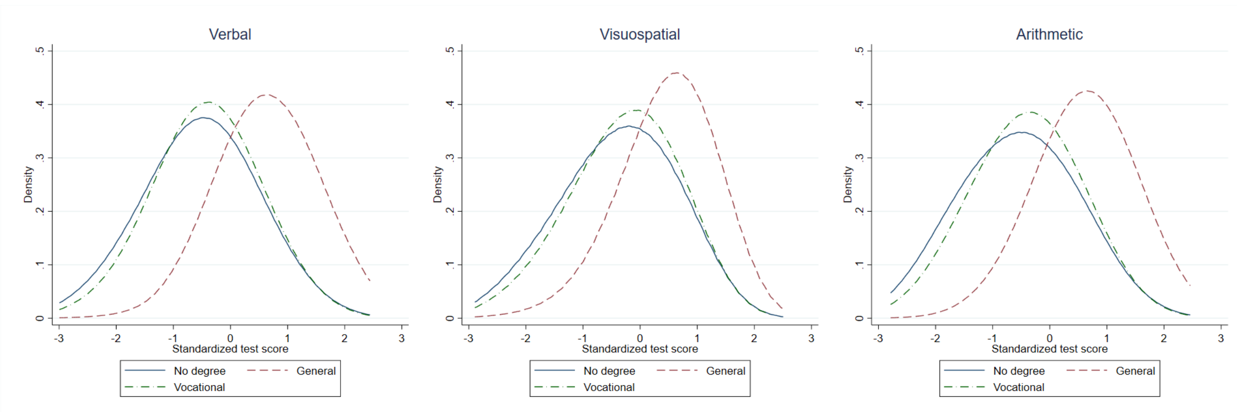
Figure 1b displays the differences in the three components of the cognitive skill test and Figure 1c in the eight components of the non-cognitive skill test. We find large differences in the cognitive skill distribution between those admitted to the general secondary schools and the other two groups.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

[6] Note that 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)

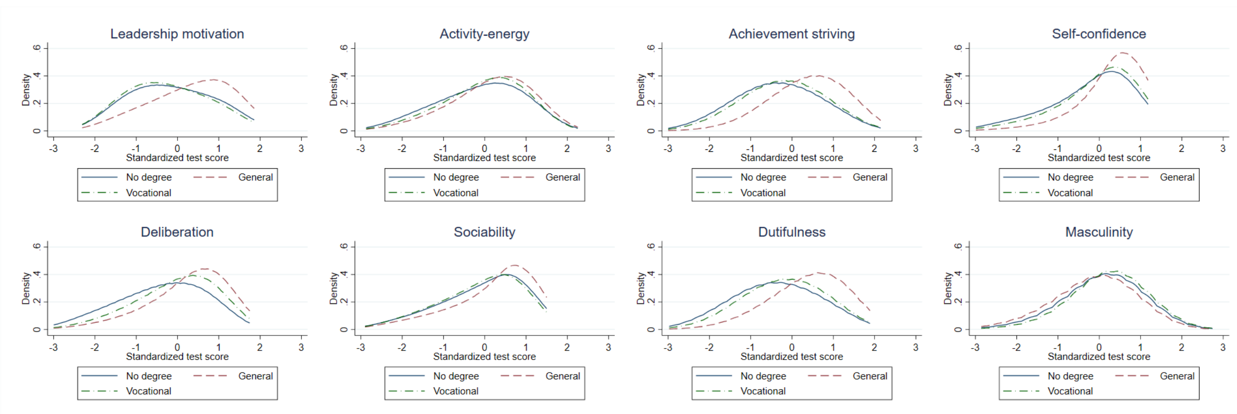
Figure 1: Distributions of test scores by education




(a)




(b)




(c)

*Note:* Figure 1 shows the distributions of the 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. Panel (a) plots the anchored test scores, while panels (b) and (c) plot the standardized scores from each subtest.

Figure 1c demonstrates that there are also large differences in several non-cognitive traits across education groups. Those who have participated in the general secondary school 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 valued at the labor market, 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 comprehensive school.

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

# 4 Identification strategy and results

## 4.1 Identification strategy

Identifying the effect 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 (eg. parent characteristics). Some of these factors can be controlled, but not all background characteristics can be measured in a reliable way. The resulting omitted variable problem generates a bias in the estimates.[7]

[7] Table A1 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

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, anchored | 10.43 | 10.23 | 10.20 |
| Non-cognitive test score, anchored | 10.35 | 10.29 | 10.26 |
| Cognitive and non-cognitive test scores, anchored | 10.47 | 10.21 | 10.15 |
| 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 |

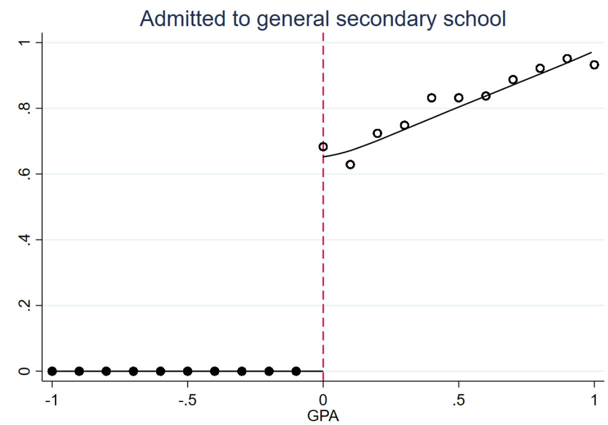
*Note:* Earnings and income are measured in 2018 euros. Parental income is the sum of the mother's and father's annual taxable incomes in 1991 to 1995.

We identify the effects of admission into general secondary education on non-cognitive and cognitive skills by using admission cutoffs in a regression discontinuity design. We compare the outcomes of students who **all applied** to these schools but ended up on different sides of the admission threshold.

General secondary schools select students based on compulsory school GPA. In the joint admission system, the students can apply up to five different programmes. We restrict our estimation sample to individuals who applied to at least one general secondary school and compare the scores of the applicant to admission threshold of the general secondary school with the lowest GPA requirement among the general programs listed in the application. The applicants who do not reach this threshold enter either a vocational secondary education

larger effects on the test scores than the RDD estimates.

Figure 2: Cutoff and admission into general secondary school




*Note:* Figure 2 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.

if such program is listed as a one of the alternatives in their application or fail to enter secondary education entirely.

The applicants scoring above this threshold are admitted to at least one general secondary school. It is still possible that they will enter vocational track if they have ranked vocational program higher in their application and if they pass the threshold of this vocational program. However, there is a large discontinuous jump at the likelihood of entering general secondary school. As shown in Figure 2 shows that being above the admission cutoff increases the likelihood of being admitted to a general school by approximately 65 percentage points.[8]

We define the cutoff for each school ($k$) in each year ($t$) as the GPA of the last accepted student. Our running variable for applicant $i$ is then defined as:

[8] While general programs select students based on comprehensive school GPA only, the vocational schools use also other admission criteria such as work experience. Vocational schools also often give different weights to grades from different subjects in the 9th grade. In our data, we only observe GPA, and have no information on these other admission criteria. This also prevents us from using DA propensity score methods suggested in (Abdulkadıroğlu et al., 2022). However, dropping all applicants who had ranked at least one vocational program above the least selective general program had no effects on the results. Note also that RDD estimates are based on applicants that are within bandwidth from the admission threshold of least selective general program listed in application i.e. the applicants that have a non-degenerate risk of being admitted to a general program.

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

where $c_{ikt}$ is the applicant's GPA and $\tau_{kt}$ 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, and estimate the following reduced form regression:

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

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 to school $k$ in year $t$, 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 error terms $e_{ikt}$ 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 effects of general secondary schooling. Using this strategy, we estimate the local average treatment effect (LATE) of general secondary school on the cognitive and non-cognitive skills. We report first stage and LATE estimates for two separate treatment variables $D_i$. The first treatment variable indicates that the applicant was admitted to general secondary education, and the second, that the applicant has completed general secondary school by the time of entering military service. 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:

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

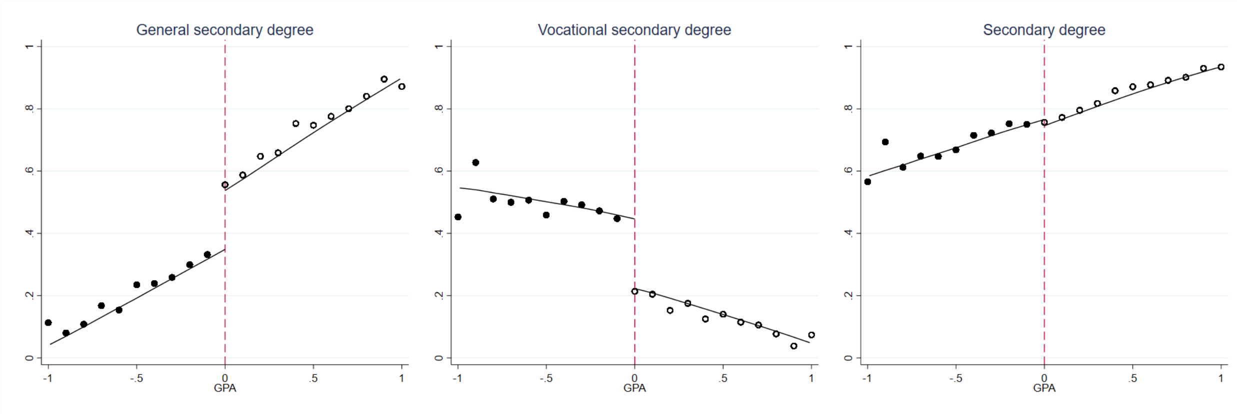
where $h$ is the bandwidth determining the observations that are sufficiently close to the threshold to be used in estimating the effect of admission. We estimate the optimal bandwidth estimated using the selection procedure in Calonico et al. (2014). However, to make estimates with different outcomes comparable, we use a bandwidth of 0.5 GPA units in all baseline specifications. [9]

## 4.2 Results

Figure 3 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 with the lowest admission criteria (dashed line in the figure). Some students who scored below this threshold still enter general secondary school either by applying directly for schools after the centralized admission system is completed or 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 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 would have been

[9]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 A2 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.

Figure 3: Admission cutoffs into general secondary school and completed secondary degrees.




*Note:* Figure 3 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.

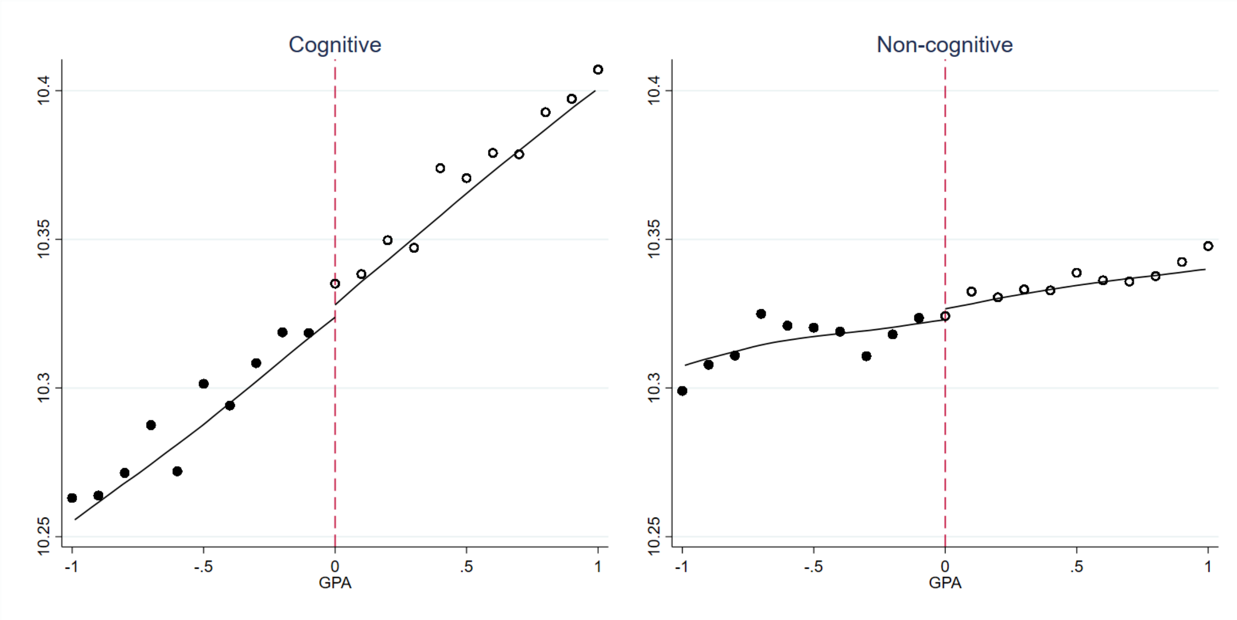
admitted to general secondary school.

The middle panel of Figure 3 shows the likelihood of completing a vocational school as a function of (re-scaled) comprehensive school GPA. This is a mirror image of the left panel. Likelihood of completing vocational training decreases with the comprehensive school GPA and displays a clear drop at entry threshold to general secondary school. The rightmost panel of Figure 3 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.

In Figure 4 we show the effect of schooling on skills - the main question analysed in this paper. While cognitive and non-cognitive skills are both positively correlated with comprehensive school GPA, cognitive skills display a stronger correlation with the comprehensive school GPA. Based on Figure 4, 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 upper general secondary school admission threshold for both skill measures.

In Table 3, we verify the validity of our approach by examining the effect of exceeding the admission threshold on pre-determined variables. According to these results, our treatment

Figure 4: Anchored test scores and admission cutoffs into general secondary education.




*Note:* Figure 4 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.

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 (see Table A3 in the Appendix).

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

In the bottom section of Table 3, we replicate the results already shown in Figure 3. 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

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) |
| | | |
| *Peer characteristics* | | |
| GPA (scale 4 to 10) | 0.818*** | (0.058) |
| Share of women | 0.149*** | (0.017) |
| Cognitive test score, anchored | 0.064** | (0.021) |
| Non-cognitive test score, anchored | 0.109** | (0.052) |
| Cognitive and non-cognitive test scores, anchored | 0.083*** | (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) |
| Attended military† | 0.018 | (0.014) |
| Age at non-cognitive test | 0.018 | (0.032) |
| Age at cognitive test | 0.040 | (0.044) |

*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.

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 universities of applied sciences rather than a degree in 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 and Virtanen (2022) who use same data for more recent cohorts to evaluate the effect of schooling on earnings.[10]

Finally, we check that exceeding the admission threshold has no significant effect on the likelihood of entering military service (and taking the test) or the age at which the test is taken. We were concerned on selection in the test score data but according to these results there is no indication that admission would have an effect on the availability or the timing of the test scores.

Additionally, we test for possible manipulation in the running variable. Figure A1 in the Appendix report GPA histograms. Figure A1(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

[10]The set-up in Silliman and 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 and 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.

Table 4: RDD estimates of the effect of general secondary education on 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

in Figure A1(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 A3 in the Appendix. These results are similar to our main estimates.

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. As noted in Section 3.4 the outcome variables are anchored to later earnings and the effects can therefore be interpreted as proportional effects on economic value of these 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

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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

effects exceeding 2% both in cognitive skills and in non-cognitive skills fall outside the 95% confidence interval. Comparing these effects to 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 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

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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

results according to which fluid intelligence is independent of learning, experience, and education.

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 strong impact on earnings and hence demonstrated value in the labor market.

In Table 6, we show the effects on the individual elements of the non-cognitive test. Again we find only one significant effect even for traits where the differences across school type are the largest suggesting again 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.

# 5 Conclusion

Admission to general vs 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 quite different - students who end up in general education have much "higher quality" peers when 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.

Taken at the face value our 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. The finding also suggests that efforts on identifying the effects of schooling on key cognitive and non-cognitive skills should focus on younger children.

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# Appendix A. Tables and Figures

## OLS estimates

Table A1 presents OLS estimates of the effects of completing the general secondary school on the anchored 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 5.6 % on non-cognitive skills and 19.4% 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 A1: OLS estimates of the effects of completing general secondary education on anchored test scores.

| | (1) Non-cognitive | (2) Cognitive | (3) All | (4) Non-cognitive | (5) Cognitive | (6) All |
|---|---|---|---|---|---|---|
| *Full sample:* | | | | | | |
| Completed general degree | 0.066*** | 0.208*** | 0.275*** | 0.019*** | 0.083*** | 0.102*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) |
| N | 143 512 | 143 512 | 143 512 | 118 427 | 118 427 | 118 427 |
| Controls | NO | NO | NO | YES | YES | YES |
| *RDD sample:* | | | | | | |
| Completed general degree | 0.031*** | 0.118*** | 0.149*** | 0.010*** | 0.040*** | 0.050*** |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) |
| N | 41 164 | 41 164 | 41 164 | 41 164 | 41 164 | 41 164 |
| Controls | NO | NO | NO | YES | YES | YES |

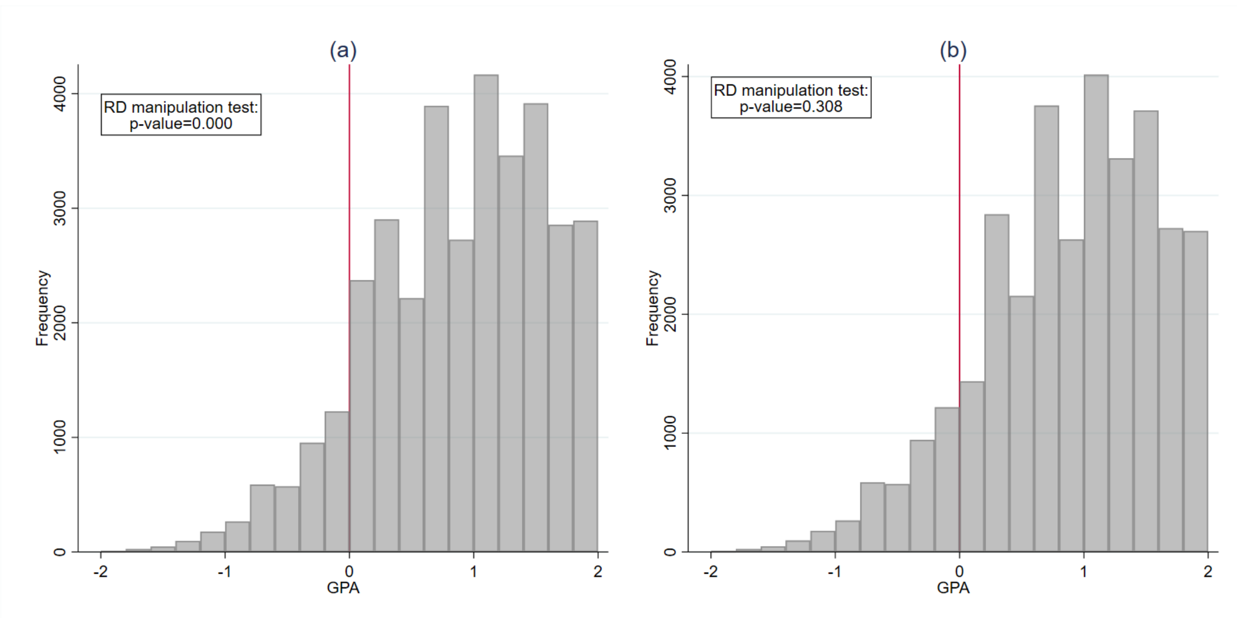
*Note:* Full sample includes men aged 18 to 22 at the end of the year in which they take the test from birth cohorts 1974-1979. RDD sample refers to the estimation sample used in our RDD estimates (see section 3.3). Control variables include dummies for .5 wide GPA intervals, age at test, age at test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

## Frequencies around the cutoff

Figure A1 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 A1: Density across the cutoff.




*Note:* Figure A1 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 A2, we estimate the effect of general secondary education on anchored 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.

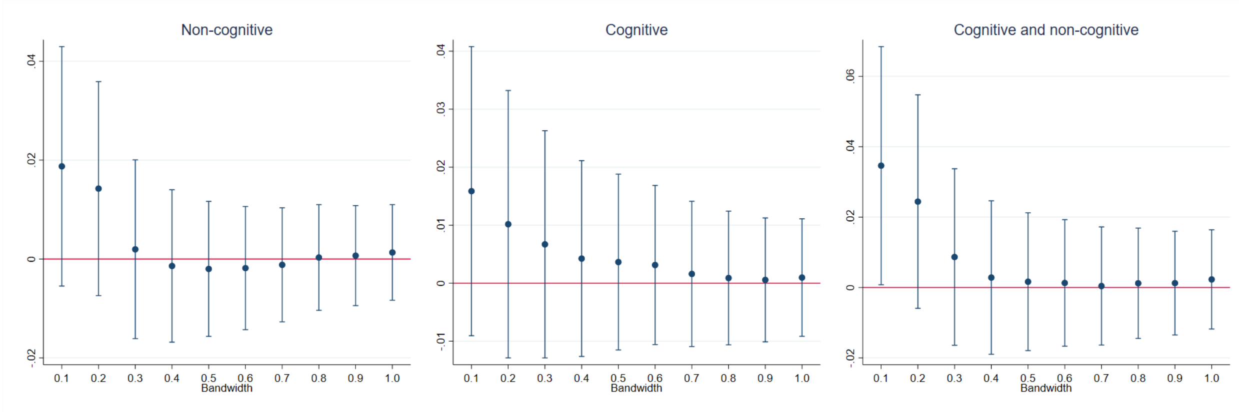
Table A2: RDD estimates of the effect of completing general secondary education on anchored test scores using optimal bandwidths

| | Non-cognitive | Cognitive | Non-cognitive and cognitive |
|---|---|---|---|
| Reduced form | -0.000 | -0.001 | -0.003 |
| | (0.006) | (0.006) | (0.009) |
| *Admission to general school:* | | | |
| First stage: | 0.585*** | 0.589*** | 0.592*** |
| | (0.021) | (0.021) | (0.021) |
| LATE: | -0.000 | -0.001 | -0.005 |
| | (0.011) | (0.011) | (0.015) |
| *Completed general degree:* | | | |
| First stage | 0.173*** | 0.163*** | 0.171*** |
| | (0.024) | (0.022) | (0.023) |
| LATE | -0.000 | -0.003 | -0.017 |
| | (0.037) | (0.039) | (0.052) |
| N | 20 363 | 17 702 | 19 913 |
| Optimal bw below/above | .30/1.20 | .47/1.02 | .34/1.19 |

*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 A2, we examine the robustness of our main estimates to different bandwidths. Figure A2 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.

Figure A2: Robustness to alternate bandwidths.




*Note:* Figure A2 plots the RDD estimates of crossing the admission threshold on the anchored 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.

In general, the estimates resemble our main results in that they are close to zero, and except for a single estimate with a bandwidth of .1 in the rightmost subfigure, also statistically insignificant.

## Additional robustness checks

In Table A3 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 A3. 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 A3 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 A3: Robustness checks

| | Non-cognitive | Cognitive | All |
|---|---|---|---|
| *Donut:* | | | |
| | -0.010 | -0.002 | -0.012 |
| | (0.011) | (0.011) | (0.015) |
| N | 7 295 | 7 295 | 7 295 |
| | | | |
| *Parental controls:* | | | |
| | -0.008 | 0.003 | -0.005 |
| | (0.007) | (0.008) | (0.010) |
| N | 7 856 | 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.