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Effect of secondary education on cognitive and non-cognitive skills[☆]

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ABSTRACT

We examine the effects of secondary education on cognitive and non-cognitive skills using admission cutoffs to general secondary schools. We measure these skills using the Finnish Defence Forces Basic Skills Test, which, due to compulsory military service, covers the vast majority of Finnish men and serves as a strong predictor of later labor market success. We find that the large differences in the average skills across men that differ in their schooling when entering military service are due to selection rather than causal effects of secondary education on either cognitive or non-cognitive skills.

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 (Borghans et al., 2008; Cunha et al., 2006). There is also evidence suggesting that the importance of non-cognitive skills has grown over time (Edin et al., 2022).

Prior literature surveyed by e.g. Almlund et al. (2011) and Currie and Almond (2011) has convincingly shown that early education interventions can have positive effects on both cognitive and non-cognitive skills. There is also some evidence showing that large-scale school reforms affecting education at early adolescense may improve cognitive skills (Brinch & Galloway, 2012; Pekkala Kerr et al., 2013) but in general evidence on later interventions on skills and, in particular, on the non-cognitive skills is much more limited than evidence on the effects of early interventions. Even the question of whether basic skills are set early in life or remain malleable during adolescence is still debated.

The content of education is a major policy decision affecting the skills learned in school. Especially, 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, in particular, when trying to respond to challenges imposed by rapid technological change. 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 (Hanushek et al., 2017; McNally et al., 2022). This hypothesis has motivated much of the research on the returns to vocational education but there is no direct evidence on the effects of general or vocational education on skills.

This paper contributes to the existing literature by using admission cutoffs to general secondary education to identify the causal effects of secondary schooling on both cognitive and non-cognitive skills, as measured by the Basic Skills Test of the Finnish Defence Forces. Exceeding the admission threshold to general schools primarily allocates applicants to different types of secondary education – academically oriented general versus vocational programs – without affecting the likelihood of completing a secondary degree. Therefore, we interpret our findings as mainly capturing the effect of the type of secondary education on skills, rather than overall effect of secondary education.

The two education tracks provide students with very different curricula and focus. General secondary schools have an ambitious

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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 types of secondary education include some academically oriented studies, but their scope and scale is much larger in the general secondary schools. Additionally, the peer groups in these programs differ significantly. Therefore, Finnish men entering military service and taking the battery of tests may have spent three years in drastically different school environments based on their 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.

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 use data on Finnish men born between 1974 and 1979 who applied to secondary education between 1991 and 1995, and performed their military service between 1995 and 1999. We demonstrate that both cognitive and non-cognitive skills are highly relevant in the labor market by showing that the military skill test scores are strongly correlated with later earnings.

Our data show significant differences in both cognitive and non-cognitive skills between men who have obtained general secondary degrees and those with vocational secondary degrees by the time they enter military service. Average cognitive skills of general 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 selection and that large differences in secondary schooling have surprisingly little impact on either cognitive or non-cognitive skills. In particular, we find no effects on the skills most strongly correlated with future earnings, such as logical, mathematical, and verbal reasoning, or on measures related to sociability, achievement motivation, and self-confidence. Interestingly, we observe that admission to general secondary school decreases measures of masculinity (i.e. tendency towards gender-typical preferences).

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. For example Hansen et al. (2004) and Winship and Korenman (1997) 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 also at a later age, both for measures of fluid and crystalized intelligence (see Carlsson et al. (2015) as an example with similar outcome measures to this study and Ritchie and 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 on earnings in Norway. Silliman and Virtanen (2022) study the impact of vocational versus general education on earnings in Finland, and Dahl et al. (2023) analyze the effects of secondary school programs on earnings in Sweden. The effect of education program on skills is one of the potential mechanisms that may explain the estimated effects on earnings in these papers, but none of them contain direct measures of skills. Other mechanisms are also possible. For example, Dahl et al. (2023) find that the effects of secondary school programs on earnings can largely be attributed to the impact of these programs on choice of occupation and the wage differences across occupations.

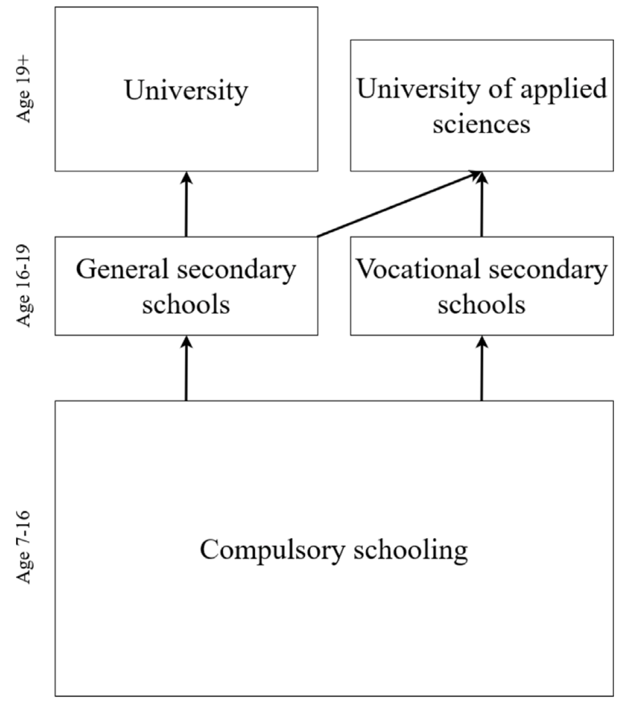

Fig. 1. Structure of the Finnish education system. *Note:* Fig. 1 shows the Finnish education system relevant to the birth cohorts in this study (1974–1979).

Our paper differs from much of the previous work by providing direct information on the effect of secondary education on skills and, in particular, also on the non-cognitive skills. Furthermore, we focus on slightly older students compared to studies based on school reforms, thus providing evidence on the malleability of basic skills at ages from 16 to 19.

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. Fig. 1 summarizes the structure of the Finnish education system.

In Finland, compulsory comprehensive school lasts for nine years and typically ends in May of the calendar year when students turn sixteen. After completing comprehensive school, most students apply for secondary education.

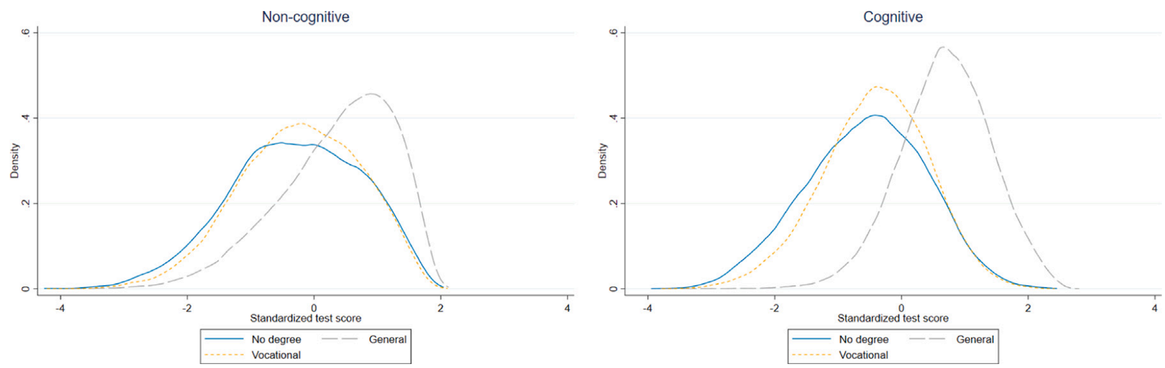

Fig. 2. Distributions of test scores by education. *Note:* Fig. 2 shows the distributions of the standardized test scores for those with no secondary education (N = 24 468), general secondary education (N = 59 394), and vocational secondary education (N = 59 572) at the time of taking the test. The sample includes men aged 18 to 22 at the end of the year in which they take the test.

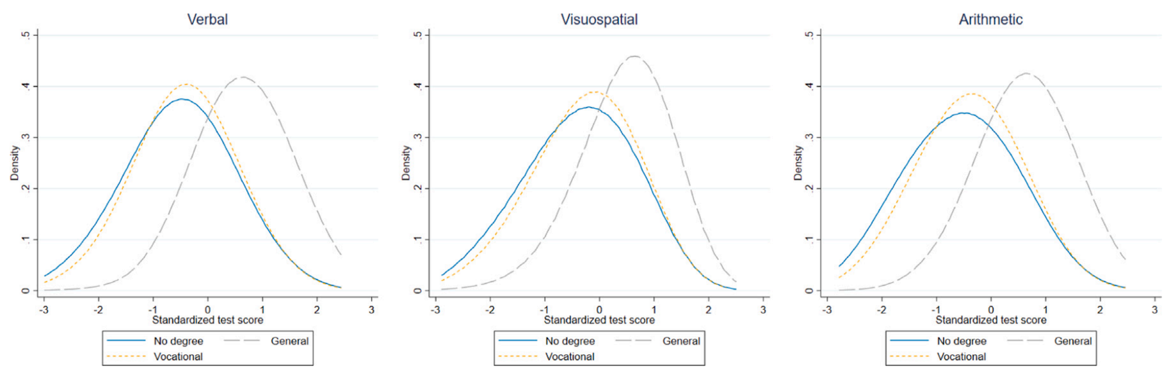

Fig. 3. Distributions of cognitive skills by education. *Note:* Fig. 3 shows the distributions of the standardized test scores for those with no secondary education (N = 24 468), general secondary education (N = 59 394), and vocational secondary education (N = 59 572) at the time of taking the test. The sample includes men aged 18 to 22 at the end of the year in which they take the test.

There are two main options at the secondary level. General secondary schools offer an ambitious academic program that prepares students for tertiary education, either at traditional universities or universities of applied sciences. Completing general program requires passing 75 courses each comprising 38 h of classroom instruction plus homework. Although the target duration is three years, students can study at their own pace, with some graduating only after four years. The general secondary education culminates in the matriculation examination, which provides eligibility for university-level studies but does not grant professional qualifications

General education students study Finnish, mathematics, natural sciences, humanities and, on average, 2.5 foreign languages. Unlike in some countries, general schools offer a relatively uniform program. Mathematics offers two levels of difficulty, and students can select additional elective courses. They can choose foreign languages from the options provided by their school, and they have both compulsory and optional courses in humanities and natural sciences. However, there are no separate tracks within general education (National Board of Education, 1994b).

The other secondary education option is vocational education that provides practical training and vocational competences in specific occupations. For the men in our sample, the most common fields of study listed as their first application requests 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 schools over 80% of training focuses on practical skills, with part of the training conducted at workplaces under the supervision of experienced workers.

Vocational secondary education also contains compulsory classes in Finnish, mathematics and one foreign language, but these classes are more limited compared to general education. For the cohorts that we study, a three-year vocational program consisted of 120 study weeks, with only 20 of those weeks dedicated to academic subjects, including compulsory classes in Finnish and mathematics.

Based on the 1995 curriculum, we estimated that the minimum requirements in general education include 2.4 times more Finnish classes, 3.2 times more mathematics classes, 5.9 times more foreign language classes, and 24 times more classes in the sciences and humanities compared to the minimum requirements in vocational education. An alternative comparison by the National Board of Education notes that the learning goals for Finnish and mathematics in vocational education roughly correspond to the content of three general school courses, whereas general secondary school requires a minimum of six courses in both subjects. This official comparison shows smaller differences than our calculation based on the proportion of Finnish and mathematics courses relative to total compulsory courses, but it still highlights a significant divergence between the practically oriented vocational secondary education and the more theoretically oriented general secondary education (National Board of Education, 1994a).

Vocational programs are 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.[2] Students can apply to up to five different school-program combinations. Admission is based on school and program -specific admission scores.

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

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 behavior.

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. 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.

We focus our analysis on individuals who apply to at least one general secondary school. Entry requirements for general secondary schools are, on average, significantly more stringent than those for vocational programs, and applicants are more likely to rank general education above vocational programs. Consequently, applicants to general secondary schools who include also vocational schools in their application are typically admitted to these programs if they fail to gain entry into a general program. For those not accepted into any secondary education programs, the main alternative 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 subsequent years, although, having completed their compulsory schooling, they are not obligated to continue their 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, for example, on-going education, health problems or family reasons), 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 is available for men who are exempt from service or those who 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 of using it for task placement during military service. However, the process proved too slow, and the conditions at testing sites were not sufficiently comparable. As a result, the Defence Forces reverted to testing conscripts at the beginning of their service (Nyman, 2007).

During the period covered in our data, 70% of men participated in military service and took the skills test battery. The sample is somewhat selective, as men with lowest comprehensive school GPA are less likely to serve in the military and to take the Basic Skills test. However, as we demonstrate later in Table 3, admission to general secondary education does not affect the likelihood of entering military service. Hence, we argue that selection into the test data is not causing bias to our results.

The test consists of two main sections: one for cognitive and one for 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 the Swedish military, as described in, for example, Grönqvist et al. (2017). It has three forty-question sets that measure verbal and numerical skills as well as logical reasoning. The logical reasoning component, based on Raven's progressive matrices, is closely related to common IQ tests.

The non-cognitive test component was developed by the Finnish Defence Forces in late 1970's and has been used in its original format from 1982 to 1999 (covers all the years we examine). This test also consists of several parts. We use data from the leadership inventory, which includes measures of eight traits that are deemed important for military leaders by army psychologists. These traits are also used by the Defence Forces for allocating individuals to different types of military training.[3] Each trait is assessed using 20 to 30 statements to which the test-taker is asked to agree or to disagree. The individual test items are not published, and the detailed content of the test is considered a military secret. Brief descriptions of each measure of the cognitive and non-cognitive tests are provided in Table A1 in the Appendix.

The test battery is quite extensive. The cognitive test has 120 items, while the leadership inventory part of the non-cognitive test has 218 items. During the years used in this study, the test was a paper and

[2] Description of the institutional context in this paper is largely based on the description in Huttunen et al. (2023).

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

pencil test that took approximately two hours to complete. We have access to raw test scores, including the number of correct answers on the cognitive test and trait indicative responses on the non-cognitive tests, but not to the individual test items.

The Defence Forces use the test results as one of the criteria for selecting conscripts for 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 with higher scores in the military tests are more educated and earn substantially more between the ages of 30 and 34. Additionally, Jokela et al. (2017) validate the measures of the leadership inventory against the more commonly used BIG5 personality test by administering short versions of both tests to a sample of students. According to their results, the subscales of the military test are highly correlated with measures of extroversion, neurotism and conscientiousness in the BIG5.

Psychological test scores do not have a natural scale. The Defence Forces aggregate the raw scores into measures of cognitive and non-cognitive skills and use a standard nine-point scale for both measures. To make the interpretation easier, we convert the raw scores to more familiar standard deviation units, so that each dimension has a mean of zero and a standard deviation of one in the cohorts used in the analysis. We use confirmatory factor analysis to estimate factor loadings between the observed raw scores and latent factors, and well as to estimate the correlations between the latent factors in a two-factor model. We then estimate factor scores that we use as outcome variables (details provided in the Appendix). After standardization, these factor scores have a mean of zero and a standard deviation of 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 method, we follow the approach 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 the predicted values from this regression as skill measures. This procedure weights the raw scores in a different way than factor analysis and, in addition to reducing dimensionality, provides 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 come from tax records available from 1987 onward. We define earnings based on annual wage earnings, excluding taxable benefits. We link the tax data across years using person identifiers and merge them with other data sources. For the main analysis, we use the average annual real earnings between ages 35 and 39, as earnings during this period are strongly correlated with lifetime earnings (Böhlmark & Lindquist, 2006). We take an average over the five-year period to reduce the effects of short-term fluctuations and instances with zero earnings during times spent outside the labor force.

The education data comes from two main sources. Information on completed degrees is from the Statistics Finland Register of Degrees and Examinations that covers all post-compulsory degrees completed in Finland. Furthermore, we have information on applications and admissions to secondary schools, as well as on grades from comprehensive school from the Joint National Application Register maintained by National Board of Education. However, this version of the data does not include information on all the admission criteria used in vocational education (see Section 2.2). Therefore, we focus solely on the effects of admission to the general education programs.[4]

We use Statistics Finland's family relation tables to link the men in the sample to their parents. Information on the parent's completed education and earnings come from the same registers as information on the men's education and earnings.

3.3. Estimation sample

We restrict our estimation sample to conscripts who take the Basic Skills Test in the year when they are between the ages of 18 and 22. This excludes those who postpone their service due to participation in college-level education and thus take the test after college (about 4% of men take the test after age 22), as well as those exempt from military service or who enter civil service (about 15% of men in our data do not have a valid test score). It is important to note, however, that the data still include most college students, as the majority of men complete 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, making them not strictly comparable to the rest of the sample. Since only about 5% of conscripts are Swedish-speakers, removing them from the sample has no effect on our main results.

Results from the full Basic Skills test are available from 1982 to 1999. The application register is available for 1985, 1989, and annually from 1991 onward. However, due to changes in the vocational education system, observations from the 1980's may not be fully comparable with later years. Therefore, we only use data from 1991 onward. To maximize sample size while maintaining comparability, we restrict our sample to cohorts who applied to secondary school between 1991 and 1995 (∼426,000 individuals). The men in our final data were born between 1974 and 1979 and completed their military service between 1992 and 1999.

As noted in Section 2.2, we lack the necessary information to calculate exact admission points for vocational education. Therefore, our analysis focuses on the effects of admission to general secondary programs. Consequently, the sample is further restricted to applicants who applied to general education (47% of all 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 exploit. Finally, we need at least two applicants on each side of the cutoffs for our RDD design. Therefore, we exclude programs that do not meet this requirement along with applicants to these programs.[5] Our final estimation sample has 41,164 male applicants across 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. Specifically, we calculate the average real income earned between ages 35 and 39 and regress this earnings measure on all cognitive and non-cognitive test scores, as well as cohort dummies.[6]

In Table 1, we report the results from these regressions. In the first column, we explain average earnings with the scores from the three subsections of the cognitive test. Although, we have access to

[4] While our data contains information on admission and graduation dates, we have no data on actual enrollment between these dates. This prevents us from reliably identifying the effects of years spent in school.

[5] We test the sensitivity of our results to the choice of estimation sample by restricting the sample to cutoffs with at least three or five applicants on each side. The results from these robustness checks are very similar.

[6] 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
Predictive power of test scores for average earnings at ages 35–39.

	(1)	(2)	(3)
Cognitive:			
Visuospatial	1540***		1380***
	(80)		(80)
Verbal	2110***		1500***
	(80)		(80)
Arithmetic	4140***		3500***
	(90)		(90)
Non-cognitive:			
Leadership motivation		1500***	800***
		(110)	(100)
Activity-energy		−390***	630***
		(90)	(90)
Achievement striving		2890***	1400***
		(80)	(80)
Self-confidence		2510***	630***
		(90)	(90)
Deliberation		840***	1430***
		(80)	(80)
Sociability		−100	1020***
		(100)	(100)
Dutifulness		730***	70
		(90)	(80)
Masculinity		−140**	100
		(60)	(60)
N	147 032	147 032	147 032
R^2	0.088	0.071	0.120

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 average annual earnings at ages 35–39 measured in 2018 euros. We do not drop zero earnings. 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.

the raw scores (i.e. the number of correct answers in each test), we have normalized these scores to have a mean of zero and a standard deviation of one for easier interpretation. These normalized scores are used as explanatory variables in the regression.

The cognitive test scores have a substantial effect on earnings with the arithmetic test scores being highly predictive of later earnings. A one standard deviation increase in the arithmetic test is associated with a 4200 euro increase in earnings at ages 35 to 39, ceteris paribus. The partial correlations of both the visuospatial and verbal tests are also positive and statistically significant. The three cognitive test scores jointly explain 8.8% of the variation in earnings between ages 35 and 39.

Table 3
Effects of crossing the general school 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	(3300)
Mother has a secondary degree	0.039	(0.025)
Father's earnings	9200*	(5200)
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[a]	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)	1.013***	(0.040)
Share of women	0.073***	(0.012)
Cognitive test score	0.521***	(0.024)
Non-cognitive test score	0.249***	(0.017)
Mother's earnings	10 500***	(900)
Mother has a secondary degree	0.082***	(0.006)
Father's earnings	24 900***	(1900)
Father has a secondary degree	0.097***	(0.007)
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	−1000**	(400)
Average annual earnings at ages 25–29	−1200	(800)
Average annual earnings at ages 30–34	200	(1000)
Average annual earnings at ages 35–39	13	(1300)
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.

[a] 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.

In the second column, we repeat the analysis using the non-cognitive test scores. These scores also show a strong correlation with future earnings. In particular, measures related to achievement motivation and self-confidence are highly correlated with future earnings. The 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. Since, the measures are generally positively correlated, the coefficients for individual measures are smaller than those in the first two columns. Despite this, the coefficients for most cognitive and non-cognitive test scores remain significant even when both scores are included simultaneously. Together, these test scores explain 12% of the 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 (Borghans et al., 2008; Edin et al., 2022; Jokela et al., 2017; Kautz et al., 2014).

3.5. Descriptive statistics

Figs. 2–4 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 took the test. For easier interpretation and readability, we display smoothed standardized scores scaled to have a mean of zero and a standard deviation of one in the 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 normally distributed. The raw scores also reveal that the test is sufficiently challenging to avoid significant ceiling effects in the cognitive scores, but they may limit the range of scores in some sections of the non-cognitive test. It is important to note that our analysis estimates the treatment effects for the compliers at the margin of admission, not for the top students who might be more susceptible to the test score ceiling. We also perform various robustness analysis that reassure us that potential ceiling effects in some subtests are not masking actual effects.[7]

Fig. 2 reveals large differences in skills across men differ in their secondary education background at the time of taking the test. Men who have completed general secondary education by the test date have much higher scores in both cognitive and non-cognitive tests than men who have completed a vocational secondary 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 secondary education are small. The differences in cognitive skills across men with different secondary schooling is substantially larger than the difference in non-cognitive skills.

Fig. 3 shows the differences in the three components of the cognitive skill test by completed secondary education. We find substantial differences in the cognitive skill distribution between those with a general degree and the other two groups. The differences are of roughly equal magnitude (about 1 standard deviation) across all three components of the cognitive skills test.

Fig. 4 demonstrates that there are also significant 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), as well as in self-confidence, deliberation, sociability and dutifulness. Since these skills are highly correlated with observed earnings, those with general education clearly are in an advantageous position. Again, we find no major differences in skills between those with vocational education and those with completed education beyond comprehensive school.

Table 2 shows the means of the key variables used in the analysis, as we all some background characteristics. In addition to the differences in test scores, there are large differences in student characteristics across groups that differ in their education at the time of the test. Men who have completed a general program have a substantially higher grade point average in comprehensive school compared to those with a vocational degree or no secondary degree (8.3 vs. 6.7 or 6.5 on scale from 4 to 10). General secondary school graduates have also more educated and higher earning parents. Furthermore, they earn approximately 50% more at ages 35 to 39 compared to men in the other two groups. In contrast, those with a vocational or no secondary degree have very similar background characteristics on average.

In the following analysis, we compare the effects of general secondary education to all other alternatives combined (without distinguishing between vocational education and no degree). This is because we are unable to determine applicants' admission success in vocational schools. However, it is reassuring that the data shows large differences in the distribution of skills and background characteristics between those with general secondary education and others, while the differences between those with vocational and those with no secondary education are minimal.

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 to 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 program and use the program with the lowest cut-off (lowest GPA requirement) of the general programs listed in their application. By construction each applicant is in data only once.

We then compare the outcomes of students who have very similar admission probability but narrowly ended up on opposite sides of each cutoff resulting in either admission to the general track or not. Those below the admission cutoffs are admitted to vocational secondary education or fail to gain access to secondary education altogether. As we demonstrate in Section 4.2, applicants who are barely accepted into a general program 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.

Applicants scoring above the general school admission cutoffs have a significantly higher probability of being admitted to a general program. As shown in Fig. 5, being above the admission cutoff increases the likelihood of being admitted to a general secondary education by approximately 65 percentage points. The fuzziness of our setting is due to several reasons. Firstly, 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 meet the threshold of that 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 may not have been contacted due to the

[7] As a robustness check, we excluded the tests that exhibit clearer sings of the ceiling effects, i.e. visuospatial, leadership motivation, self-confidence, and sociability tests, when calculating the factor scores and used these scores as the outcome variable. The results remain very similar. Additionally, we performed a robustness check where we make ceiling effects more severe by further restricting the range of scores and truncating the distribution by an additional 10%. Again, the results are very close to our main results.

[8] Table A3 summarizes OLS estimates of the effect of graduating general secondary school on test scores, using different sample restrictions and control variables. In general, the OLS estimates show significantly larger effects on test scores than our RDD estimates.

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

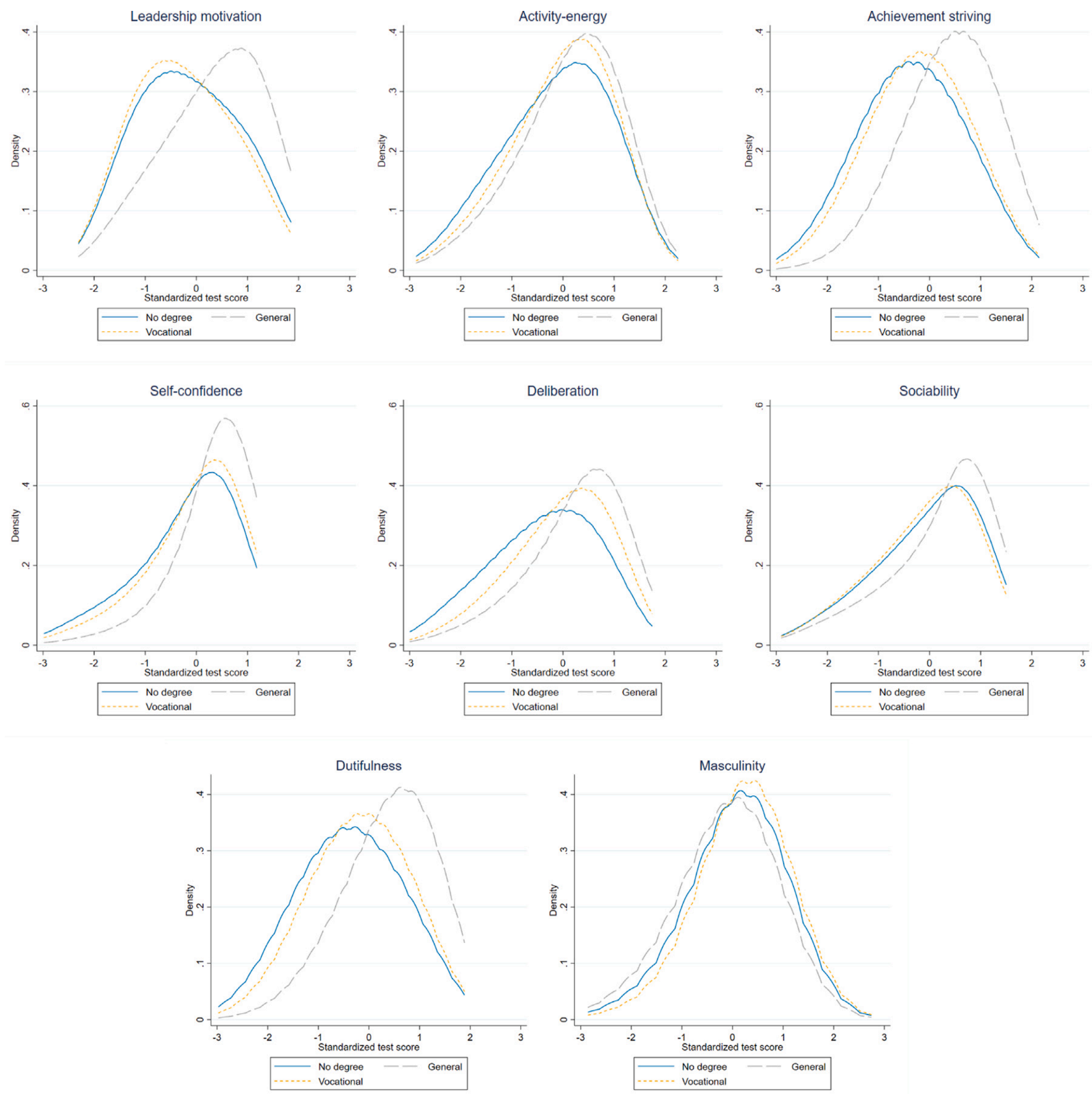

Fig. 4. Distributions of personality traits by education. *Note:* Fig. 4 shows the distributions of the standardized test scores for those with no secondary education (N = 24 468), general secondary education (N = 59 394), and vocational secondary education (N = 59 572) at the time of taking the test. The sample includes men aged 18 to 22 at the end of the year in which they take the test.

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 the probability of admission to general education (see discussion below).

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's 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]:

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

where y_{ikt} is the test score for applicant i to program 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

[10] Since we are unable to detect how applicants perform with respect to the admission cutoffs in vocational schools, we are not able to fully account for the application preferences as suggested in Abdulkadiroglu et al. (2022). With this exception, we follow their approach.

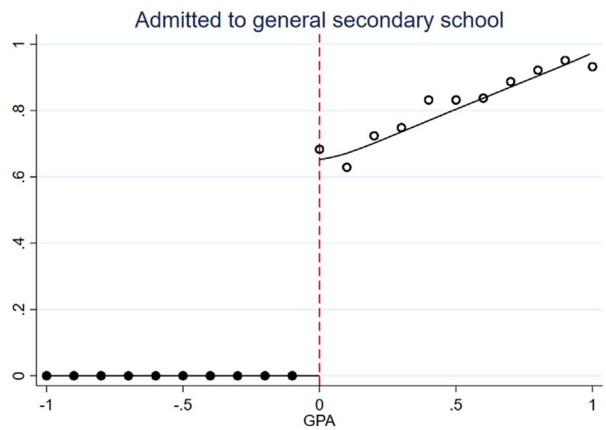

Fig. 5. Cutoff and admission into general secondary school. *Note:* Fig. 5 shows the share of applicants admitted to general secondary education, plotted against the program-specific running variable. The dots depict sample means of the dependent variable for 0.1 GPA unit wide bins. The lines show local linear regressions weighted using an edge kernel and bandwidth 1.

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), where we scale the reduced form estimates by either admission to a general secondary school or completing a general degree by the time of taking the test. In both cases crossing the admission cutoff is used as an instrument. The first stage of this fuzzy RD design is Eq. (2) where the outcome variable is D_i measures how being above the admission cutoff increases the likelihood of admission or graduation. The second stage measures the effect of admission or graduation on cognitive and non-cognitive skills.

We employ non-parametric local linear regression with triangular kernel weights centered at admission cutoffs:

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

where h is the bandwidth determining the observations that are sufficiently close to the thresholds to be used in the analysis. 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 fixed bandwidth of 0.5 GPA units for our baseline specifications. RDD estimates using optimal bandwidths are reported in the Appendix.[11]

Fig. 6 illustrates the effect of exceeding the general program admission threshold on completed degrees. The likelihood of completing different secondary degrees by the time of entering military service varies significantly with comprehensive school GPA. However, crossing the general program cutoff clearly increases the likelihood of completing a general secondary degree, while the likelihood of completing a vocational degree drops by a similar magnitude. Finally, the rightmost panel of Fig. 6 confirms that exceeding the general secondary school admission threshold primarily affects the type of school attended rather than the total amount of schooling. We interpret these findings as evidence that our main estimates mainly capture the effect of general versus vocational education on skills, rather than the effects of completing any secondary education.

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 strategic behavior. We perform also various empirical checks to study the validity of the research design.

In Table 3, we verify the validity of our design by examining the effect of exceeding the general education admission threshold on several pre-determined variables. According to these results, our treatment is uncorrelated with mother's earnings, 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 is well balanced around the admission threshold.

We also check that exceeding the admission cutoff to general education 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 one unit (roughly one standard deviation). The share of women among classmates increases by 7 pct. 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 Fig. 6. Exceeding the admission threshold increases the likelihood of completing general secondary school by about 20 pct 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 and 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)

[11] Optimal bandwidths vary between 0.3 and 1.3 depending on the outcome. In general, the optimal bandwidths are lower below the admission thresholds than above. Table A5 presents our main RDD estimates using the optimal bandwidths. In Figure A5, we further test the robustness of our results by using fixed bandwidths ranging from .1 to 1 GPA unit. Our results remain consistent across bandwidth choices, except when using the very smallest bandwidths.

[12] 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.

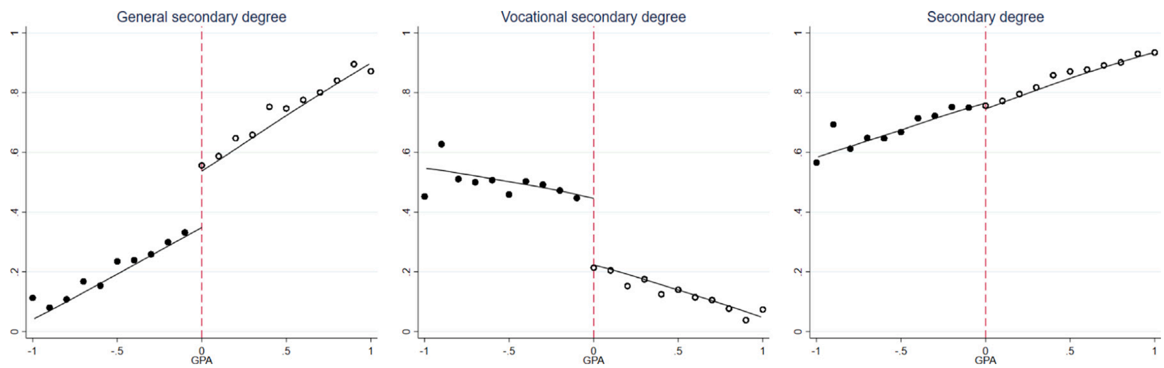

Fig. 6. Admission cutoffs into general secondary school and completed secondary degrees. *Note:* Fig. 6 shows the share of students completing a general secondary degree, a vocational secondary degree, or either of these by the test date, plotted against the program-specific running variable. The dots 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.

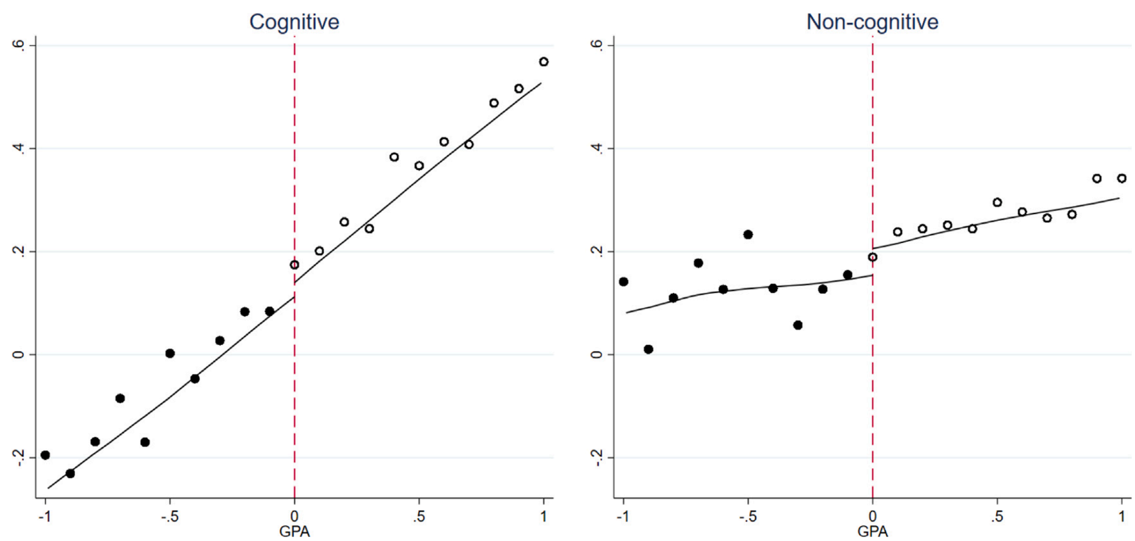

Fig. 7. Test scores and admission cutoffs into general secondary education. *Note:* Fig. 7 plots the anchored test scores against the program-specific running variable. The dots depict sample means of the dependent variable for 0.1 GPA unit wide bins. The lines show local linear regressions weighted using an edge kernel and bandwidth 1.

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 A6 in Appendix. These results are similar to our main estimates.

5. Results

5.1. Main results

Fig. 7, illustrates the impact of crossing admission cutoffs to general secondary schooling on skills. Both cognitive and non-cognitive skills are positively correlated with comprehensive school GPA, with a stronger correlation for cognitive skills. However, only a slight increase is observed at the admission threshold for both skill measures, suggesting that admission to a general program has minimal, if any, effect on either type of skills.

Our main results are presented in Tables 4, 5, and 6. First, Table 4 reports the effects of general secondary schooling on aggregate measures of cognitive and non-cognitive skills.

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	8322	8322

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	8375	8375	8375

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

According to the results, general education has no significant causal effect on cognitive or non-cognitive skills.[13] The reduced form estimates are, not only insignificantly different from zero, but also small in magnitude (2% of a standard deviation for both skills). Similarly, the IV estimates for admission to general school and a completed general degree are small and not statistically significant.

These results suggest that the large differences in average skills among men that differ in the secondary schooling (reported in Table 2) are primarily due to selection rather than the effects of secondary education on skills. The reduced form estimates are relatively precise so that effects exceeding 10% of a standard deviation in cognitive skills and effects exceeding 13% of a standard deviation in non-cognitive skills fall outside the 95% confidence interval. In contrast, the IV estimates, particularly when crossing the admission cutoff is used as an instrument for obtaining a general degree, are much less precise. For non-cognitive skills, the upper bound of the 95% confidence interval is slightly larger than the mean difference by completed secondary degree. For cognitive skills, however, the upper bound of the IV estimates' 95% confidence interval remains clearly larger than the raw difference in means.

Table 5 presents the results for the individual test sections of the cognitive test. Given the lack of effects on the aggregate skill measures, it is unsurprising that we also find no effects on the sub-test scores. Similarly, Table 6 shows the effects on the individual elements of the non-cognitive test. Once again, the effects of general education on the tested traits is not significantly different from zero, even for the traits where the differences among men with different secondary education are the largest, such as leadership and achievement motivation. The only effect that is statistically significant is a negative effect of general education on masculinity. It is perhaps not surprising that admission to a general secondary school decreases the masculinity indicator, which measures the tendency towards gender-typical preferences, as general programs involve much greater exposure to female classmates compared to vocational programs.

Since the cognitive skills test has three dimensions and the non-cognitive test eight, testing this many hypothesis separately may generate false positives. Our main approach to address this issue involves aggregating the 11 test scores into two dimensions. Additionally, we calculate q-values (Anderson, 2008) to control for false discovery rates. The effect on masculinity remains borderline significant after adjusting for multiple hypothesis testing (q = 0.06).

In the Appendix, we test the robustness of our results in a number of ways. In Table A4, 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 potentially impact our findings. However, the estimates in Table A4 align with our main results and leave our conclusions unaltered. Next, we test the sensitivity of our main results to different bandwidth choices. Table A5 uses optimal bandwidths for each of our main outcomes. These estimates closely resemble our main results. Figure 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 A6, 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 affects our result.

5.2. Interpretation of the results

According to our results, admission to general secondary education has very little effects on cognitive and non-cognitive skills measured in the military tests at age 19 or 20. There are at least three possible explanations for the findings. Perhaps the test does not measure relevant skills, perhaps these skills are no longer malleable at late adolescence, or perhaps there is a lot of heterogeneity in the effects, i.e., education type still affects skills, but just not for those at the admissions margin examined here.

The Defence Forces Basic Skills Test clearly measures quite basic arithmetic and verbal skills, rather than more advanced abilities like differential calculus or essay writing. However, it is important to note that these basic skills are strongly correlated with later earnings, demonstrating their value in the labor market. The test also appears to measure the skills with sufficient accuracy, otherwise the test results would not be associated with later earnings to the extent displayed in Table 1. Hence, we are confident that the military tests capture skills highly relevant in the labor market. Furthermore, similar measures have been used in earlier studies (e.g., Carlsson et al. (2015)).

It is also possible that relevant cognitive and non-cognitive skills are fixed at an earlier age and are no longer malleable at secondary school age. Furthermore, our 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. (e.g. Almlund et al. (2011), Carlsson et al. (2015) and Cattell (1971)).

Finding that general secondary education has no effects on arithmetic and verbal abilities is probably the most surprising. There are much more mathematics and reading and writing assignments in general secondary school curriculum compared to vocational schools. These results appear also contradict prior work examining the effects of the amount of schooling. For example, Carlsson et al. (2015) find that an additional year of secondary schooling increases verbal skills by 21% of a standard deviation and improves technical comprehension by 14% of a standard deviation. Brinch and Galloway (2012) estimate that one year of schooling in adolescence increases IQ by 3.7 points (25% of a standard deviation). Furthermore, in their meta-analysis, Ritchie and Tucker-Drob (2018) conclude that one year of schooling raises cognitive skills by 1 to 5 IQ points (7%–33% of a standard deviation). Our reduced form estimates (2.2% of a standard deviation), and even the IV estimates for a completed degree (11.9% of a standard deviation) on cognitive skills are smaller than the results in these studies, although admittedly, our IV estimates are rather imprecise.

[13] We explore heterogeneous treatment effects by parental education and prior school performance (9th grade GPA). The estimates for any of the subgroups do not differ significantly from our main estimates.

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

Comparing our results to those of previous studies is challenging. While most prior research focuses on the effects of time spent in school, in our study crossing the cutoff to general program primarily allocates applicants to different secondary schools. Nonetheless, admission to general education still results in a significant increase in time spent on academically oriented studies (as described in Section 2.1). Furthermore, crossing these cutoffs place applicants into distinct school environments with different peer groups. Students in general schools typically have higher prior school performance, come from more highly educated families, and are more often women. Given the substantial differences in the curriculum and school environment, we might expect the admission to general school to impact skills.

Comparison to studies examining the effects of schooling on non-cognitive skills is even more difficult because of the variety of skill measures used and the scarcity of studies. Heckman et al. (2006) discovered that men who achieved 13 years or more of education exhibit an increase of .35 standard deviations in internal locus of control and .7 standard deviations in self-esteem compared to individuals with less than 12 years of schooling. Compared to these numbers, our estimates of the effect of secondary schooling on non-cognitive skills are much smaller.

However, finding that general secondary schooling has no effect on skills for the students at the margin of admission does not imply that the effect of secondary schooling is close to zero for all students. It is possible that there is a lot of heterogeneity in the effects of schooling on both cognitive and non-cognitive skills. Our analysis focuses on applicants who are at the margin of being admitted to general secondary schools. These students are near the middle of the academic ability distribution and among the last to gain access to general secondary schools. Even though we find no effects for this subgroup, it does not imply that for example the best students would not benefit from a more academic program. The effects on students at the margin of admission remain relevant parameter, particularly for discussions on expanding or reducing admission quotas in the general secondary schools.

6. Conclusion

We examine the effects of secondary education on cognitive and non-cognitive skills by using admission cutoffs to general secondary schools. Exceeding the general secondary school admission threshold primarily affects the schooling path without affecting the likelihood of completing any secondary degree. Rather than impacting overall graduation from secondary education, admission to general education leads to substantial differences in the curriculum and school environment. General education is academically oriented, preparing students for higher education, while vocational education focuses on practical, occupation-specific skills. In addition to the large differences in the curricula, peer groups in these secondary education programs differ significantly — students in general education tend to have 'higher quality' peers, as measured by average school grades, test scores, and parents' education levels. Moreover, the proportion of female classmates is significantly higher in general education compared to vocational education.

Our results indicate that general secondary education has little effect on the skills measured in the military tests at age 19 or 20 for the applicants at the margin of admission. Given the substantial differences in school environments and in the average skills among men with differential secondary degrees, these findings are somewhat surprising. However, finding no effect on the skills of marginal applicants does not imply that differences in secondary education have no effect on all students. Our estimation sample includes applicants who are among the last applicants to gain access to general secondary programs, representing those applicants that are near the middle of the academic ability distribution. Hence, general education might still benefit, for example, more academically oriented students whose preferences and abilities align better with academic content. Nevertheless, our findings are quite striking as they show that, for applicants at the margin, important cognitive and non-cognitive skills are not much affected by substantial differences in schooling during adolescence.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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All authors approved the version of the manuscript to be published.

Appendix A. Additional figures and tables

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econedurev.2024.102603.

Data availability

The authors do not have permission to share data.

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