Bank of Israel Research Department

The Effect of Teachers' Cognitive Skills on Students' Educational Achievements[1]

Edith Sand[*] and Guy Levy[**]

Discussion Paper 2025.04
May 2025

Bank of Israel – http://www.boi.org.il

[1] We thank the Israeli Central Bureau of Statistics for allowing restricted access to data in the CBS Research Laboratory. We also benefited from comments from Yann Bramoule, Cecilia Garcia Penalosa, Adrien Bouguen, Celine Poilly, Tanguy van Ypersele, Naomi Friedman-Sokuler, Elad Demalach, Noam Zussman, Sefi Bahar, Tamar Ramot-Nyska, Eyal Argov and participants at seminars at Bank of Israel and at Aix-Marseille School of Economics.

[*] Edith Sand – Bank of Israel, Research Department Email: edith.sand@boi.org.il
[**] Guy Levy – Bank of Israel and Hebrew University Email: guy.levy@boi.org.il guy.levy3@mail.huji.ac.il
Corresponding author at: Bank of Israel, Israel. E-mail address: edith.sand@boi.org.il (E. Sand).

חטיבת המחקר, בנק ישראל ת״ד 780 ירושלים 91007
Research Department, Bank of Israel. POB 780, 91007 Jerusalem, Israel

השפעת הכישורים הקוגניטיביים של מורים למדעים על הישגי תלמידיהם

אדית זנד וגיא לוי

תקציר

אנו בוחנים את השפעתם של מדדים שונים לכישורים הקוגניטיביים של מורים למדעים—כגון תואר אקדמי מתקדם, ציון הבגרות במתמטיקה, וציון החלק הכמותי של הבחינה הפסיכומטרית—על הישגיהם הלימודיים של תלמידיהם. באמצעות נתונים מנהליים מפורטים על תלמידי כיתה י״ב ומוריהם לבגרות במקצועות המדעים בין השנים 2012 ל-2019, אנו מוצאים כי לכישורים הקוגניטיביים של המורים—ובעיקר לאלו הנמדדים באמצעות ציון הבגרות במתמטיקה—יש השפעה מובהקת וחיובית הן על הישגי התלמידים בטווח הקצר, כפי שמשתקף בציוני הבגרות שלהם במקצועות המדעים, והן על הישגיהם בטווח הארוך, כגון הסיכוי ללמוד באוניברסיטת מחקר והסיכוי לבחור בלימודי STEM (מדעים, טכנולוגיה, הנדסה ומתמטיקה). נוסף על כך, נמצא כי מורים בעלי כישורים קוגניטיביים גבוהים יותר תורמים לשיפור משמעותי בהישגי התלמידים, במיוחד בקרב תלמידים בעלי יכולות גבוהות ובהתאם להתאמה מגדרית בין המורה לתלמיד.

מילות מפתח: מדיניות ממשלתית, תשואה לחינוך, השכלה גבוהה.

The Effect of Teachers’ Cognitive Skills on Students' Educational Achievements

Edith Sand and Guy Levy

Abstract

We investigate the effects of various measures of science teachers' cognitive skills—based on academic degrees, math matriculation scores, and psychometric math scores—on their students’ educational achievements. Utilizing detailed administrative data of 12th grade students and their science teachers, spanning the years 2012 to 2019, we find that teachers' cognitive abilities—mainly those measured by math matriculation scores—have clear and positive effects on both students' short-term matriculation test scores and several long-term measures of academic success, such as the probability of pursuing post-secondary studies at a research university and the probability of choosing a STEM major subject. Additionally, teachers with higher cognitive abilities are shown to lead to higher gains, particularly among students with stronger aptitude and same-gender student-teacher matching.

Keywords: Government Policy, Returns to Education, Higher Education.

1. Introduction

Around the entire world, on an almost daily basis, children and adolescents attend schools of various types, where they invariably encounter teachers. Students' prolonged and consistent exposure to teachers, which often constitutes a significant portion of their first two decades of life, may have a substantial impact on their human capital and, consequently, on shaping the economy and the market. For this reason, teacher quality is often considered a significant factor in the educational system, while some studies have found that teacher quality is the most crucial school-related factor affecting student achievement, outweighing other factors such as class size and overall educational spending (Rivkin et al., 2005; Darling-Hammond, 2000).

Research on the relationship between teachers' qualifications and teacher effectiveness has been ongoing for several decades, emphasizing the importance of both cognitive and noncognitive characteristics of teachers. Teachers' social skills, such as motivation, pedagogical abilities, and interpersonal communication, have been found to be central factors in shaping the personal and academic development of students (Rockoff et al., 2011). Various recent studies have also found that several proxies for teachers' cognitive abilities, such as intelligence, basic skills, content knowledge, and academic success, are positively correlated with teacher effectiveness, and help explain the gaps in their students' educational achievements.

This study examines how the cognitive skills of high school science teachers affect their students' short- and long-term academic achievements. To the best of our knowledge, the effects of teachers' cognitive abilities have not been examined in the Israeli context, despite this subject's importance for education policy. The insufficiently high level of Israeli teachers' cognitive skills, as recently confirmed in international assessments (PIAAC 2014-2015), has often been raised in public debate as one of the central reasons for the significant lag in Israeli students' achievement in these assessments (Hanushek et al., 2019). The recently reported shortage of teachers in the education system might further weaken Israeli students' international standing.[1]

This gap in the educational achievements of students in Israel compared to other OECD countries is one of the policy challenges facing the Israeli economy. The lag in Israeli educational achievements becomes even more pronounced when focusing on STEM

[1] See for Example: Knesset Research and Information Center (2023). "Teacher Shortage – A Review" (in Hebrew).

subjects (science, technology, engineering, and mathematics), which are crucial for technological innovation and growth in economic productivity. The level of mathematical and scientific literacy of Israeli students is among the lowest in the OECD, as shown by PISA test performances. Additionally, the achievement gaps based on students' socio-economic backgrounds are among the widest in OECD countries.[2]

In the past decade, however, there has been moderate improvement in most of these measures. PISA tests reveal a slight improvement in Israeli students' relative scores, though their achievement remains in the bottom third, especially in mathematics and science. The gaps based on students' socioeconomic backgrounds have also narrowed slightly. Similar trends are observed in Israel's matriculation exam scores. The percentage of students pursuing advanced matriculation courses in science subjects increased between 2012 and 2019, while the gap based in students' socioeconomic backgrounds remained largely stable (Figure 1a).

Among other things, these recent developments can be attributed to two educational programs conducted in Israel during these years aimed at strengthening the study of sciences and mathematics, primarily in high schools. The first program, called the Technological- Scientific Reserve Program, was implemented in 2011, and the second, called the National Program for Strengthening Mathematics Studies, was implemented in 2015.[3]

Both programs increased the budget allocated to math and science studies to boost the number of students pursuing these fields in high school and enhance their knowledge. Concurrently, steps were taken to increase the number of teachers in these subjects and elevate their cognitive abilities. This included raising the number of teaching students in these fields in university by providing incentives for institutions and students, encouraging the retraining of professionals from the engineering and high-tech fields to teaching, and establishing M.A. degree programs in science teaching to enhance existing teachers' knowledge and improve their lesson plans.

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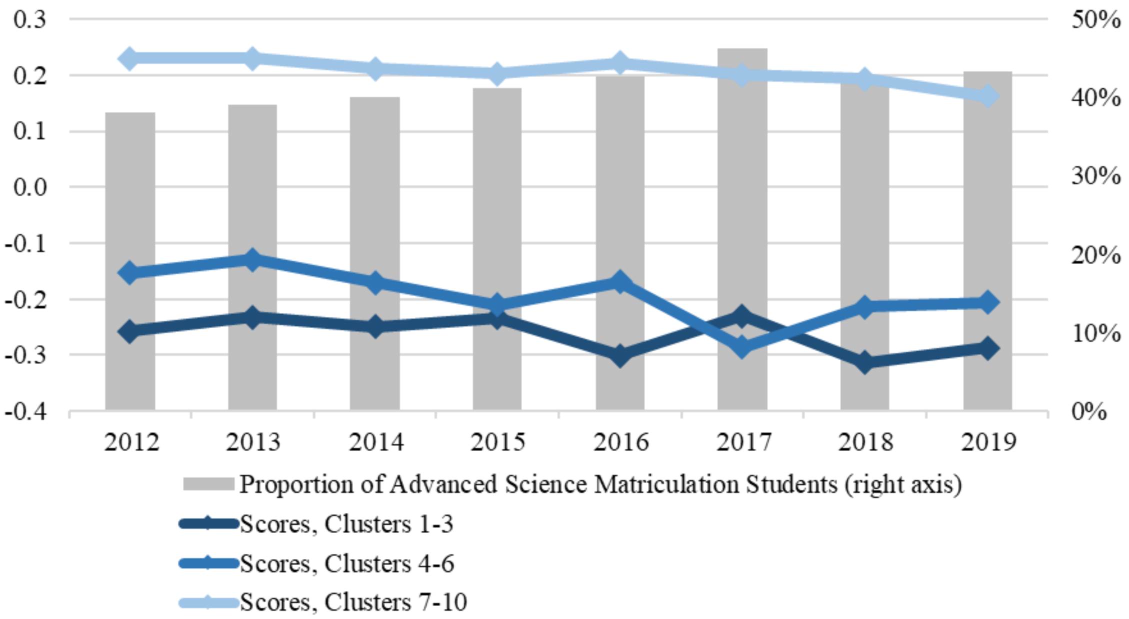
[2] PISA 2018 Results (Volume I): What Students Know and Can Do, PISA, OECD Publishing, Paris; OECD (2021). Education at a Glance 2021, OECD Indicators, OECD Publishing.

[3] For more details on these programs, see the Scientific-Technological Reserve Program and the National Program for Strengthening Mathematics Studies. There was another national program, the 'Significant Learning' reform that was implemented from 2015 onwards. Among other things, this program changed the requirements for obtaining a matriculation certificate by limiting the maximum number of compulsory subjects that students can take at an advanced level of five credit units or more.

Figure 1a:
Proportion of Students Examined in Science Matriculation Subjects and Their Scores by Socioeconomic Cluster, 2012–2019



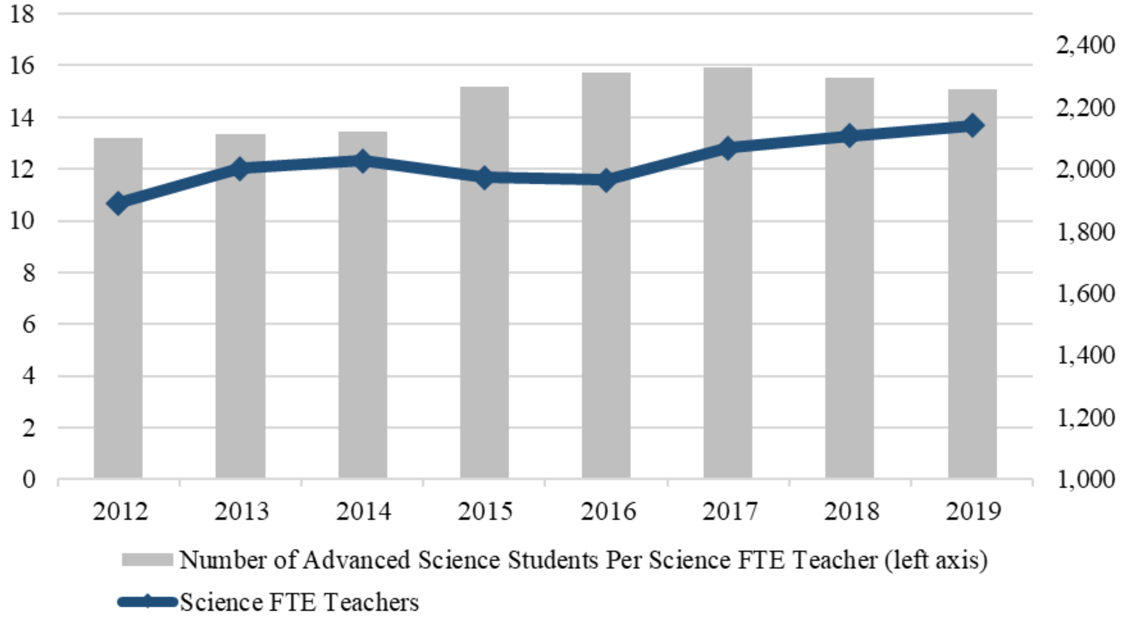
Notes: Advanced science students are students examined in a science matriculation subject at the level of at least 5 credit units. Scores are standardized based on the graduation cycle and the subject, including all examined students. The Socioeconomic Index characterizes and classifies localities and local authorities in Israel according to the socioeconomic level of their residents in the following areas: demographic composition, education, standard of living, employment, and benefits. The socioeconomic clusters included in this paper are constructed based on data from the 2015 national survey, and are ranked between 1 and 10 (where 10 is the highest socioeconomic outcome).

These programs did succeed in increasing the number of students pursuing advanced matriculation courses in science subjects and the number of teachers in these fields in the past decade. However, the increased demand for science studies was not fully met by the supply of teachers, resulting in an increased ratio of advanced level students to full-time science teachers throughout the period (Figure 1b).[4] Despite the increased shortage of teachers in those subjects, the steps taken to raise the cognitive abilities of teachers were effective. Several proxy indicators for teachers' cognitive abilities show positive results. The proportion of teachers with a master's degree or higher increased, as did their average math matriculation exam scores and psychometric[5] math exam scores (Figure 1c).

[4] The total number of science students per full-time-equivalent science teacher increased in the first part of the period and then declined due to the implementation of the 'Significant Learning' reform in 2015, which decreased the number of students who took a low-level science matriculation course.

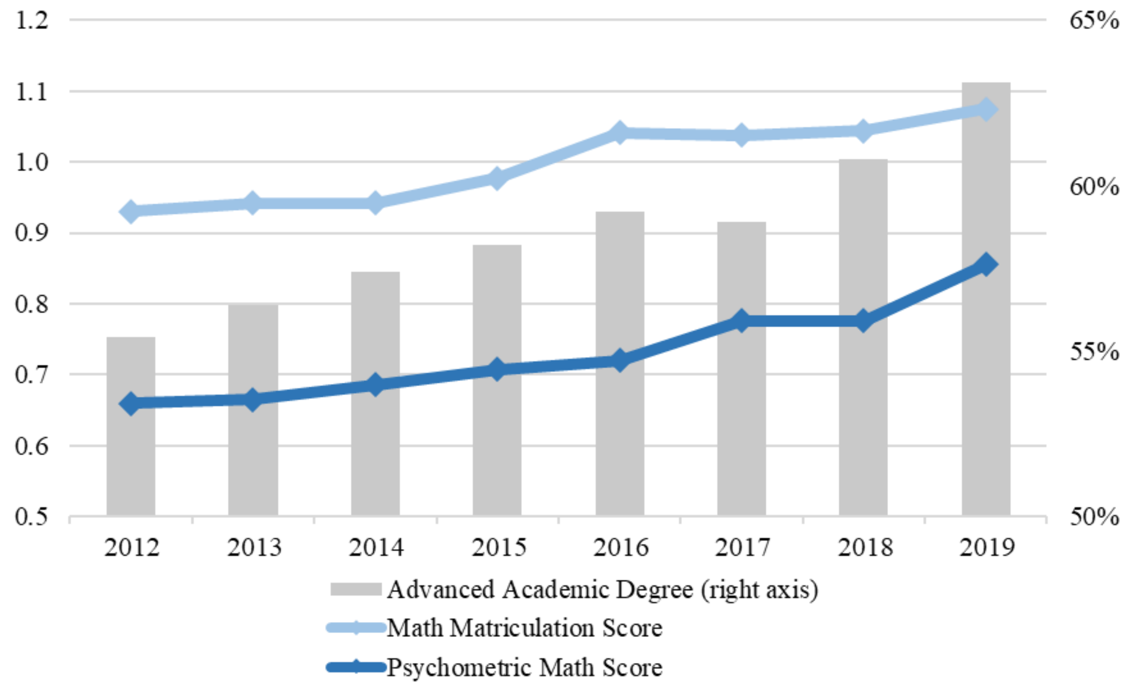
[5] The psychometric exam is an Israeli exam taken in place of the American SAT, with a similar purpose.

Figure 1b:
Number of Advanced Science Students Per Science Full Time Equivalent (FTE) Teacher and Total Number of FTE Teachers, 2012–2019



Notes: The science teacher FTE is calculated by dividing the total FTEs of science teachers by the number of advanced science students.

Figure 1c:
Cognitive Abilities Measures of Science Matriculation Teachers, 2012–2019



Notes: Advanced academic degree is a Master's degree or a Ph.D. The math matriculation scores are weighted and include bonuses based on the number of credit units taken, as computed by the Ministry of Education and the universities, then transformed into Z-scores by graduation cycle and subject (one standard deviation equals ~150 points). The psychometric math scores are standardized by test year (one standard deviation equals ~20 points).

The success of these programs in improving students' achievements in mathematics and science, as documented in the literature (Zussman and Maagan, 2019, Rimon and Romanov, 2012), raises the question of how much the increase in teachers' cognitive abilities contributed to it. This question is particularly important given the strong correlation between students' STEM matriculation test scores and their lifetime earnings (Harpaz-Mazuz and Karil, 2017), as well as the performance of knowledge-intensive industries (Bental, Somkin, and Peled, 2019).

Additionally, this research question is important for understanding the impact of educational inputs on the education system as a whole. The significant increase in demand for teachers in the Israeli education system in recent years has not been fully met. This has created a shortage of teachers across the entire education system and a decline in the cognitive abilities of new teachers entering the system (Bank of Israel, 2019a), a trend that has accelerated since the COVID-19 crisis.[6] Therefore, understanding which characteristics are important to the learning process, and their relative importance, can help design a more effective and incentivizing salary scheme for teachers.

The purpose of this study is to examine the effect of science teachers' cognitive abilities on their students' academic achievements. We utilize three proxies for teachers' cognitive abilities. The first is the attainment of advanced academic degrees (a master's degree or higher), the second is the teachers' math matriculation exam scores at the end of high school, and the third is psychometric math section scores. We suggest a gross distinction between cognitive abilities that are more acquired and refer to general knowledge in the context of sciences and those that are more innate in their nature and require more specific math-oriented capabilities. Thus, with regard to our three proxies, we view the advanced academic degree measure as representing the former set of abilities, the psychometric math scores measure as representing the latter set of abilities, and the math matriculation scores measure as placed somewhere in between.

We use administrative data of 12th-grade students who studied at least one science matriculation subject and their science teachers for the years 2012–2019. Student data were merged with teacher records, including demographics, qualifications, and unique identifiers, ensuring precise matching for science subjects. Since the database does not include the assignment of teachers and students to classes, we focus on a subsample of

[6] The decrease in the cognitive abilities of new teachers entering the education system was discussed in the Bank of Israel Annual Report for 2018, Chapter 6: "Government Services: Developments in the Education Budget and Teaching Quality in Recent Years".

teachers who are the only ones teaching the subject as part of matriculation exam preparation in their schools. Relying on the change in science teachers' cognitive ability measures over time due to the implementation of the above-mentioned reforms, we use variations in the cognitive ability indicators of science teachers at the school locality level and their changes over time to examine their impact.

Our identification strategy, which controls for general locality characteristics, is similar to the identification strategies used in other studies on this topic. Several studies have examined the effects of teachers' cognitive abilities by comparing teachers from the same locality or educational institution (Clotfelter et al., 2006; Goldhaber, 2007; Rockoff et al., 2008). Other studies rely on panel data of multiple subjects' test scores for each student, allowing general student characteristics to be held constant (Grönqvist and Vlachos, 2015; Clotfelter et al., 2016; Hanushek et al., 2018). In some studies, the dataset even allows for the control of general teachers' characteristics for those who teach multiple subjects (Metzler and Woessmann, 2012; Bietenbeck et al., 2018).[7]

These identification strategies reduce the endogeneity problem that arises because teachers are likely to be matched to students in nonrandom ways based on their general characteristics. To assess the extent of the influence of the selection of students to teachers/professions on our results, we conduct a series of sensitivity tests. Additionally, we estimate the model using an alternative method, Propensity Score Matching, to further reduce selection bias.

Our study indicates that teachers' cognitive ability indicators have clear and positive effects on both students' matriculation test scores in the short term and several measures of long-term academic success. Testing the joint effects of all cognitive ability indicators reveals the importance of teachers' math matriculation scores compared to other cognitive skills. Furthermore, we find an interesting heterogeneous pattern: Students with stronger aptitude benefit more from improved teacher credentials. Additionally, the effects vary based on the gender of both teachers and students, as well as according to student-teacher gender match.

[7] Including student and teacher fixed effects is mostly feasible at lower education levels, where teachers often teach multiple subjects. Using international assessments of the numeracy and literacy skills of primary school students and their teachers, a few papers have managed to separate the impacts of teachers' verbal and quantitative skills on their students' same-subject test scores.

Our research expands upon prior literature on the effects of teachers' cognitive skills in several ways. First, our study examines the effects of high school teachers' numerical cognitive abilities on students' performance in science subjects. Most studies have investigated the effects of teachers' general cognitive abilities without distinguishing between literacy and numeracy skills, and have focused mainly on early educational stages. Although this literature documents only small effects of teachers' cognitive skills on student performance, the results contain substantial variation across domains and educational stages. Teachers' numerical cognitive abilities have been found to have significantly positive effects on their students' performance, especially in STEM subjects (Grönqvist and Vlachos, 2015; Andrew et al., 2005; Blue et al., 2002; Amato et al., 2018; Boyd et al., 2008; Goldhaber et al., 2013 and 2017). These effects are stronger in higher grades, where the importance of teachers' content knowledge in complex material is more substantial. To our knowledge, Clotfelter et al. (2010) and Goldhaber et al. (2017) are the only studies investigating how STEM teacher credentials affect student achievement in high grades. Clotfelter et al. (2010) find that high school math students score higher if their teacher has a high licensure test score, while Goldhaber et al. (2017) show that middle school teachers' subject-specific skills are much more predictive of student achievement than basic skills test scores, especially in higher grades.

Second, our dataset allows us to test the joint impacts of several cognitive ability measures and their relative importance for student performance. Proxies for teachers' cognitive abilities investigated in the literature include psychometric scores, knowledge tests such as college entrance exams or licensure exams, years of experience, and academic background. However, few papers compare all these measures in a common setup. One such paper is Rockoff et al. (2011), which finds that both teachers' psychometric scores and math knowledge have a significant effect on teaching. Another is Clotfelter et al. (2010), which shows that among experience, educational background, and licensure test scores, the latter is the most influential characteristic on student achievement. Evidence from Goldhaber et al. (2017) reinforces this conclusion.

Third, our paper investigates the influence of cognitive ability measures on various high-stakes educational performances not only in the short term but also in the long term. This leads to important economic implications, including: the probability of acquiring higher education, the quality of that education (whether it is a research university), and its orientation (whether the major is a STEM subject).

The rest of the paper is organized as follows. Section 2 describes the data, Section 3 discusses the identification strategy, and Section 4 reports the results. Section 5 offers a summary and conclusions.

2. Background and Data

2.1 Data Sets

In this paper, we use data on high school students who studied at least one science matriculation subject and their teachers during the years 2012–2019. We constructed several measures of teachers' cognitive abilities and tested the impact of exposure to teachers with varying levels of cognitive abilities on their students' short-term performance at the end of high school and on several long-term post-secondary schooling outcomes, six years after the exposure took place.

We utilize detailed administrative files obtained from the Israeli Ministry of Education. The basic population for which the data were received includes all 12th-grade students, covering the years 2012 to 2019. We merge the students' data with matriculation exam score files for all the cohorts studied. Matriculation exams are national exams in core and elective subjects, taken between the tenth and twelfth grades. Students choose to be tested at various levels of proficiency, with each test awarding from one to five credits per subject, indicating the depth of study in the subject and the number of study hours. Some subjects are mandatory, taken at a basic level of two or three credits. Advanced level subjects carry five credits or more. To be eligible for a matriculation certificate, students must be examined not only in compulsory subjects but also in at least one subject at an advanced level of five credit units or more. The total number of credit units examined in all subjects must be at least 21. To meet these conditions, most students study and are examined in at least one advanced level subject offered by the school.[8] The advanced level subjects offered by schools are influenced by both the institution's willingness to teach the subject and its compliance with the Ministry of Education's requirements and safety

[8] As noted above, the 'Significant Learning' reform was implemented in 2015. Among other things, it changed the requirements for obtaining a matriculation certificate by limiting the maximum number of compulsory subjects that students can take at an advanced level of five credit units or more. The reform led to the cancellation of most elective study tracks at levels lower than five credit units. In our sample, the reform is reflected starting from 2017, the first 12^{th}-grade cohort to which the reform applied. For this reason, our sample for all the years 2012–2019 is restricted to STEM matriculation students at a minimum level of five credit units.

guidelines. We focus on matriculating schools[9] that offer students the option of choosing a science subject as an elective advanced level subject. To examine students' short-term outcomes, we focus on students who took an advanced level matriculation course in one of the four science subjects: Biology, Physics, Chemistry, and Computer Science. The grades were transformed into z-scores by year and subject.[10]

To study students' long-term outcomes, the student dataset was additionally merged with academic student files obtained from the Ministry of Education. These files include several post-secondary schooling variables such as the type of institution and the field of study. Based on these data, variables for each student were generated, capturing whether they started their studies up to six years after the end of high school[11], the type of institution attended (whether it is a research university) and the field of study (whether the major subject is one of the STEM subjects[12]). Each student record also contains demographic information (focusing on gender, number of siblings, father's years of schooling, mother's years of schooling, new immigrant status, and four ethnicity indicators: born in or parents born in Asia/Africa, Europe/America, Former Soviet Union, or Israel), prior test scores

[9] We therefore exclude schools that do not offer a matriculation diploma, such as *Haredi* (ultra-Orthodox) schools or special care schools.

[10] Not all schools teaching matriculation subjects offer students the option of choosing a STEM subject as an elective advanced level subject (82% of schools in the years 2012–2019). STEM subjects are usually studied at an advanced level of five credit units, but in certain subjects, such as Computer Science, there may be study programs with a higher number of credit units. Additionally, some students might obtain a lower number of credit units either due to incomplete exams or studying at a lower level in the first place. Although we do not know the exact number of students who drop out (sample attrition), the percentage of students who drop an advanced level course and take only part of the exams or study at a lower level is about 15%.

[11] It should be noted that most of the non-*Haredi* Jewish population serves in mandatory military service immediately after completing the 12th grade or, with a one-year deferment, engages in volunteer work or studies in religious or nonformal education frameworks. As a result, the minimum age for starting higher education for this population group is around 22 for males and 21 for females, approximately four and three years after completing high school, respectively.

[12] The STEM subjects included are Mathematics, Statistics, Biology, Engineering, and Medicine.

(GEMS tests)[13] and school characteristics (district[14] and locality[15] identifier, socioeconomic clusters[16]), and a religiosity indicator (Arab, Religious Jewish, or Secular Jewish).

We then merged the student dataset with teacher files, also obtained from the Israeli Ministry of Education. We restructured the teacher files in a similar manner to our student dataset, such that each record is a combination of teacher, subject, school, and year, while we focus on teachers who teach at least one of the four science subjects at matriculating schools as part of the matriculation preparation. To match exclusively between students and their teacher, we restricted the sample to teachers who uniquely teach a specific science matriculation subject at a school in a given year, meaning there are no parallel teachers teaching the same subject at that school×year.[17] This restructuring enabled us to combine the student dataset with teacher files based on the subject×school×year identifier. From these teacher files, we obtained the following information: years of experience, education level, teaching hours (in terms of Full-Time Equivalent hours), and teachers' demographic information (focusing on age, gender, number of children, new immigrant status, and four ethnicity indicators: born in Asia/Africa, Europe/America, Former Soviet Union, or Israel). It is worth noting that teachers for advanced matriculation subjects usually accompany

[13] The GEMS records (Growth and Effectiveness Measures for Schools) include test scores of fifth and eighth graders of half of the schools in Israel each year, so that each school participates in GEMS tests once every two years. The tests are taken in four subjects (Hebrew, English, mathematics, and science), thus we standardize their scores in each subject, year and grade, and then average them for each student. The final standardized GEMS score considered for each student is the average 8th grade score (or earlier 5th grade score for those with no 8th grade GEMS test score), accounting for the scores of 80% of the students in our sample. For more information on the GEMS, see the Division of Evaluation and Measurement website (in Hebrew): http://cms.education.gov.il/educationcms/units/rama/odotrama/odot.htm

[14] The geographic districts are the districts in which the locality of an educational institution is located, according to the six districts into which the State of Israel is divided (based on the Israeli Central Bureau of Statistics definitions). For more details see: https://www.cbs.gov.il/en/settlements/Pages/default.aspx?mode=Machoz

[15] A locality unit in our sample is defined as a place that is permanently inhabited with at least 40 adult residents, has a self-government and its establishment has been approved by the planning institutions (based on the Israeli Central Bureau of Statistics definitions). In our sample there are 166 localities.

[16] The Socioeconomic Index characterizes and classifies localities and local authorities in Israel according to the socioeconomic level of their residents. The socioeconomic level of a population is measured by a combination of its basic characteristics in the following areas: demographic composition, education, standard of living, employment, and benefits. The socioeconomic clusters included in this paper are constructed based on data from the 2015 national survey and are ranked between 1 and 10. For more information, see: https://www.cbs.gov.il/en/subjects/Pages/simsEx.aspx?url=https://boardsgenerator.cbs.gov.il/Pages/ESMSmetadata/Descriptions.aspx?pirsum=1&subject=28dcdc8a-9462-4314-834d-8ff5908f66d2&sims=&l=English&format=json&flat=false.

[17] On the other hand, students can learn more than one science subject and thereby be affected differently by the cognitive skills of teachers in each subject.

students from the first year of high school (typically 10th grade). Therefore, we assume that students are exposed to their teachers at least a year before they take the main part of their matriculation exams, and typically for the entire high school period.

We constructed three measures of teachers' cognitive ability for each teacher in our sample, based on additional datasets. The first measure is a dummy variable indicating whether the teacher holds a master's or doctorate degree, based on the formal education level variable obtained from teachers' files. It should be noted that, according to Ministry of Education regulations, to pursue professional teaching in high school, teachers must hold a master's or doctorate degree in a relevant field of instruction from an institution recognized and approved by the Ministry of Education. Furthermore, teachers are required to have a relevant pedagogical qualification, which involves a subject-specific teaching certificate obtained from an accredited teacher training institution in Israel. However, the Ministry of Education also approves teaching licenses for certain subjects, especially in STEM subjects, even for those without master's or doctorate degrees and in fields that are broadly related to science, such as an academic degree in science teaching.[18] In practice, data indicate that only about 60% of science teachers in the years 2012–2019 held a master's or doctorate degree, and only 50% of them had an advanced academic degree in STEM subjects.[19] This low percentage of teachers with STEM academic degrees is not surprising given the low qualification of high school math teachers recently documented in Israel.[20] These findings highlight that the measure of having an advanced academic degree represents more general cognitive skills in the context of teaching sciences. The two additional measures of cognitive ability are teachers' math matriculation test scores at the end of high school[21] and their psychometric math test scores. Since the initial matriculation test score file is from 1993 and the initial psychometric test score file is from 1991, these data cover only younger teachers. Therefore, we restrict the sample of teachers

[18] See the Ministry of Education Circular regarding teaching licenses (December 1996) for more details: Ministry of Education Circular, pp. 6-7; 18 (in Hebrew). In addition, temporary changes in regulations occasionally facilitate the criteria, allowing candidates with only a bachelor's degree to apply for a teaching license, for example in Chemistry and Biology.

[19] These data include information on teachers’ academic degrees acquired abroad. Moreover, we assume that there are no differences in the quality of academic degrees acquired abroad compared to those obtained in Israel, provided they are recognized by the Ministry of Education.

[20] Press Release: Teaching Staff in the Education System (2020/21), Israeli Central Bureau of Statistics [in Hebrew].

[21] To account for the difficulty gap between different levels of study, math matriculation test scores are weighted and bonuses are added based on the number of credit units taken, as computed by the Ministry of Education and universities. These grades are then transformed into z-scores by each year and each subject.

to those aged younger than 37 to present the effects of the different measures of teacher cognitive skills on the same population of teachers.[22] It is important to note that these two measures are significant factors in the admission process for candidates pursuing higher education in science, implying that they can also be important for the science teaching profession.[23]

The final merged dataset of students and their teachers for the years 2012–2019 includes three measures of science teachers' cognitive ability; science students' matriculation test scores; an indicator for enrollment in post-secondary schooling up to six years after the end of high school; indicators for the quality and orientation of this post-secondary schooling; previous test scores (GEMS scores in 5th and 8th grade); and students', schools', and teachers' characteristics. The final dataset is then pooled for the four science subjects: Biology, Physics, Chemistry, and Computer Science.

2.2 Summary statistics

The schools in our sample are high schools that offer at least one advanced matriculation course in one of the following science subjects: Biology, Physics, Chemistry, or Computer Science. The teacher sample is restricted to young teachers who exclusively teach a specific science matriculation subject at their school. Consequently, the sample primarily includes smaller schools, with an overrepresentation of Arab schools. Comparing school characteristics within each sector reveals that students in our sample have marginally lower socioeconomic backgrounds but largely resemble the national average within each sector.

The statistics of our sample are summarized in Table 1 for students, and Table 2 for teachers and schools. Each year, the sample consists of approximately 130 schools, representing about one-fifth of all high schools that teach at least one of the four science subjects in matriculating schools. The sample comprises around 2,500 students and 150 teachers per year. Thus, the number of advanced-level science students per school is about 18. The samples of students' and teachers' characteristics are relatively stable overtime.

[22] First, we restrict the sample to teachers who uniquely teach a specific science matriculation subject at school×year and then we further restrict the sample to younger teachers.

[23] In most Israeli universities, priority in admission to STEM fields of study is given to applicants with high matriculation scores in STEM subjects and high psychometric math scores. See, for example, the threshold conditions for admission to STEM subjects at Ben-Gurion University [in Hebrew]: https://www.bgu.ac.il/welcome/ba/reception-section-lobby?term=%D7%A4%D7%99%D7%A1%D7%99%D7%A7%D7%94&interests=10&semesters=012025 [updated October 13, 2022]).

To further understand the characteristics of science students and teachers in the schools' sample and its representativeness, we compared them to similar advanced-level science students and teachers in other schools that offer at least one advanced science matriculation course, categorized by sector, as detailed in Appendix Table A1. Panel A presents the characteristics of advanced-level science students; Panel B, the characteristics of schools; and Panel C the characteristics of science teachers, separately for the Jewish and Arab population. The age limit for teachers implies fewer schools from the Jewish sector are included in the sample, because most of the non-*Haredi* Jewish population serves in mandatory military service, which delays their entry into the labor market. Although there is an overrepresentation of Arab schools in the sample (52% compared to 30% of Arab schools in the sample of all science matriculating schools), the sample is largely representative within each sector.

Table 1
Summary Statistics of Sample Students' Characteristics by Cohort

	2012	2013	2014	2015	2016	2017	2018	2019
Students' Characteristics								
Number of Siblings	4.11	4.58	4.71	4.34	4.12	4.15	3.60	3.78
	(2.57)	(2.79)	(2.86)	(2.72)	(2.55)	(2.65)	(2.32)	(2.45)
Proportion of Female Students	0.62	0.64	0.67	0.63	0.61	0.61	0.61	0.63
	(0.49)	(0.48)	(0.47)	(0.48)	(0.49)	(0.49)	(0.49)	(0.48)
Proportion of Jewish Students	0.31	0.21	0.26	0.30	0.33	0.35	0.45	0.34
	(0.46)	(0.41)	(0.44)	(0.46)	(0.47)	(0.48)	(0.50)	(0.47)
Ethnicity[1]								
Proportion of Asia-Africa	0.17	0.15	0.16	0.21	0.20	0.24	0.28	0.20
	(0.38)	(0.36)	(0.37)	(0.41)	(0.40)	(0.43)	(0.45)	(0.40)
Proportion of America-Europe	0.10	0.06	0.07	0.08	0.10	0.09	0.11	0.09
	(0.31)	(0.23)	(0.26)	(0.27)	(0.30)	(0.28)	(0.31)	(0.29)
Proportion of Former Soviet Union	0.06	0.05	0.06	0.06	0.06	0.06	0.10	0.09
	(0.23)	(0.21)	(0.24)	(0.23)	(0.24)	(0.23)	(0.30)	(0.28)
Proportion of Israel	0.67	0.75	0.71	0.65	0.64	0.62	0.51	0.62
	(0.47)	(0.44)	(0.46)	(0.48)	(0.48)	(0.49)	(0.50)	(0.48)
Father's Years of Schooling	12.30	11.71	11.67	12.16	12.04	12.20	12.55	12.40
	(3.87)	(3.83)	(3.94)	(3.88)	(3.72)	(3.53)	(3.38)	(3.48)
Mother's Years of Schooling	11.83	11.16	11.17	11.67	12.06	12.02	12.77	12.43
	(4.14)	(4.15)	(4.21)	(4.15)	(3.78)	(3.75)	(3.54)	(3.69)
Previous GEMS Test Score[2]	0.35	0.16	0.22	0.35	0.27	0.19	0.30	0.29
	(0.71)	(0.75)	(0.76)	(0.64)	(0.75)	(0.80)	(0.72)	(0.71)
Total Number of Students	2,026	2,038	2,042	2,052	2,329	2,776	2,522	2,798
Number of Students Per School	18.17	16.44	17.60	17.59	17.84	20.24	16.84	17.69
	(15.93)	(14.34)	(14.81)	(14.86)	(14.83)	(15.77)	(12.01)	(11.14)

Notes: This table presents summary statistics of the sample students—12th-grade students in advanced-level science matriculation, whose science matriculation teacher is aged below 37, and uniquely teaches the subject at the school.

1. Students born, or with parents or grandparents born, in Asia/Africa, Europe/America, the Former Soviet Union, or Israel.
2. The GEMS records (Growth and Effectiveness Measures for Schools) include test scores of fifth and eighth graders of half of the schools in Israel each year, so that each school participates in GEMS tests once every two years. We standardized these GEMS test scores in each of four subjects (Hebrew, English, mathematics, and science), year, and grade, and average them for each student. The final standardized GEMS score considered for each student is the average 8th grade score (or earlier 5th grade score for those with no 8th grade test score).

Standard deviations are reported in parentheses.

Table 2
Summary Statistics of Sample Teachers' and Schools' Characteristics by Cohort

	2012	2013	2014	2015	2016	2017	2018	2019
Panel A: Teachers' Characteristics								
Age	31.70	31.28	31.86	31.07	31.32	31.69	31.47	31.19
	(3.37)	(3.77)	(3.40)	(3.31)	(3.41)	(3.56)	(3.24)	(3.13)
Proportion of Immigrants	0.05	0.04	0.06	0.05	0.08	0.04	0.05	0.05
	(0.21)	(0.20)	(0.24)	(0.22)	(0.27)	(0.21)	(0.22)	(0.22)
Proportion of Female Teachers	0.63	0.63	0.66	0.61	0.64	0.65	0.73	0.72
	(0.48)	(0.48)	(0.48)	(0.49)	(0.48)	(0.48)	(0.44)	(0.45)
Proportion of Jewish Teachers	0.40	0.34	0.36	0.41	0.44	0.42	0.50	0.43
	(0.49)	(0.48)	(0.48)	(0.49)	(0.50)	(0.49)	(0.50)	(0.50)
Number of Children	3.32	3.13	2.97	2.95	2.71	2.58	2.56	2.16
	(1.86)	(1.81)	(1.80)	(1.76)	(1.82)	(1.87)	(1.87)	(1.64)
Ethnicity[1]								
Proportion of Asia-Africa	0.18	0.16	0.15	0.16	0.12	0.12	0.13	0.08
	(0.39)	(0.37)	(0.36)	(0.37)	(0.33)	(0.33)	(0.34)	(0.28)
Proportion of America-Europe	0.08	0.06	0.05	0.07	0.07	0.09	0.10	0.08
	(0.27)	(0.23)	(0.21)	(0.26)	(0.26)	(0.29)	(0.30)	(0.28)
Proportion of Former Soviet Union	0.03	0.04	0.05	0.06	0.08	0.05	0.06	0.06
	(0.17)	(0.20)	(0.22)	(0.23)	(0.27)	(0.22)	(0.24)	(0.24)
Proportion of Israel	0.71	0.74	0.75	0.71	0.72	0.74	0.71	0.77
	(0.46)	(0.44)	(0.43)	(0.45)	(0.45)	(0.44)	(0.45)	(0.42)
Total Number of Teachers	130	141	132	139	148	156	154	178
Panel B: Schools' Characteristics								
Socioeconomic Cluster of School Locality[2]	3.69	3.39	3.60	3.53	3.85	4.39	4.03	3.99
	(2.05)	(1.89)	(1.95)	(2.15)	(2.25)	(2.11)	(2.01)	(2.12)
Proportion of Jewish-Religious Schools	0.24	0.26	0.23	0.27	0.28	0.23	0.28	0.23
	(0.43)	(0.44)	(0.42)	(0.44)	(0.45)	(0.42)	(0.45)	(0.43)
Proportion of Peripheral Schools[3]	0.62	0.59	0.58	0.59	0.55	0.58	0.55	0.52
	(0.49)	(0.49)	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)	(0.50)
Total Number of Schools	112	114	106	116	119	129	137	145

Notes*:* This table presents summary statistics of the sample teachers—science matriculation teachers aged below 37, who uniquely teach a science subject at the school—and of the sample schools.

1. Teachers born, or with parents born, in Asia/Africa, Europe/America, the Former Soviet Union, or in Israel.
2. The Socioeconomic Index characterizes and classifies localities and local authorities in Israel according to the socioeconomic level of their residents. The socioeconomic level of a population is measured by a combination of its basic characteristics in the following areas: demographic composition, education, standard of living, employment, and benefits. The socioeconomic clusters included in this paper are constructed based on data from the 2015 national survey, and are ranked between 1 and 10 (where 10 is the highest socioeconomic outcome).
3. The periphery indicator equals one if the geographic district is far from the population centers defined as the Central District, Tel Aviv District, Haifa District, and Jerusalem District.

Standard deviations are reported in parentheses.

Comparing the statistics of the sample schools to those of schools offering at least one advanced science matriculation course in both sectors (i.e., Columns 1 and 3 for the Jewish sector and Columns 2 and 4 for the Arab) reveals only minor differences in both sectors. Students in our school sample have a higher number of siblings (average of 4.15 compared to 3.26 in the science schools in the Jewish sector and 4.65 compared to 4.06 in the Arab sector) and lower parental schooling levels (average of 12.14 years of father's schooling compared to 13.54 years in the Jewish sector, and 11.2 years compared to 11.7 years in the Arab sector; similar gaps are found for mother's years of schooling). They are also more likely to be female in the sample schools, especially among the Jewish population (63% compared to 55% in the science schools in the Jewish sector and 64% compared to 63% in the Arab sector).

These factors contribute to a marginally lower overall socioeconomic background in the sample schools as measured by the school's socioeconomic cluster area (an average of 5.1 compared to 5.7 in the science schools in the Jewish sector and 2.7 compared to 2.9 in the Arab sector). Schools in our sample are also more peripherally located, particularly in the Jewish sector (65% compared to 40% for the science schools, with percentages of around 80% in both groups in the Arab sector). Similarly, science teachers in our school sample are relatively young (43 compared to 50 in the Jewish sector, and 38 compared to 41 in the Arab sector), and the overall proportion of female teachers resembles the national average (marginally lower in the Jewish population, 66% compared to 68%, and higher in the Arab population, 50% compared to 46%).

The statistics of the three measures of teachers' cognitive skills in our sample are presented in Appendix Table A2. There is considerable variation in the cognitive skill measures of teachers in our sample.[24] In the next section, we will exploit this significant variation to examine whether teachers' cognitive abilities have short- and long-term effects on students' academic outcomes.

3. Identification and Estimation

The primary objective of this paper is to investigate how science teachers' cognitive abilities impact their students' educational achievements. Our dataset allows us to analyze

[24] The ranges of these measures are as follows. The percentage of teachers holding an advanced academic degree is 32%; the mean of standardized math matriculation test scores is 1.14 among the teachers in our sample, ranging from min=-1.56 to max=2.34 and the standard deviation is 0.76; and the mean of the standardized psychometric math scores is 0.68, ranging from min=-1.7 to max=2.52. The Pearson correlation coefficients of advanced academic degree with math matriculation test scores and with psychometric math scores, in our short-term sample, are 0.065 and 0.11, respectively, and 0.61 between math matriculation test scores and psychometric math scores.

these effects on students' matriculation exam scores at the end of high school, as well as to track students' progress in higher education, including outcomes such as the probability of pursuing post-secondary education up to six years after high school, the quality of education obtained (attendance at a research university), and the orientation of their studies (whether in STEM subjects).

Relying on the change in science teachers' cognitive ability measures over time due to the implementation of the two educational reforms ("Technological-Scientific Reserve Program" and the "National Program for Strengthening Mathematics Studies”), we use variations in the cognitive ability indicators of science teachers at the school locality level and their changes over time to examine their impact. Additionally, we control for a range of student and school characteristics, including students' prior achievements, family background, and characteristics of schools and teachers.

In our primary empirical model, we assume that matriculation test scores and other long-term educational outcomes are determined by the following equation:

$$(1) \quad y_{ijklt} = \alpha + \beta_j + \delta_l + \gamma_t + \theta x_i + \mu x_{kt} + \sum_{n=1}^{3} \tau_n A_{nkt} + u_{kt} + \varepsilon_{ijklt}$$

where y_{ijklt} denotes the outcome of student i, taught subject j by teacher k in school locality l and in year t; β_j is the subject fixed effect; δ_l is the school's locality fixed effect; γ_t is the year fixed effect; x_i is a vector of students' characteristics; x_{kt} is a vector of schools and teachers' characteristics; A_{nkt} where $n \in \{1,2,3\}$ is one of the three measures of teachers’ cognitive ability[25]; u_{kt} is the error term in the equation, and includes a teacher-specific random element that allows for any type of correlation within observations of the same teacher; and ε_{ijklt} is an individual random element.

The coefficients of interest are τ_n, which capture the effect of the various teachers’ cognitive skills. We will also consider a specification where we include all three measures of teacher's cognitive skills separately in different regressions to test for their collinearity and relative importance for students’ educational outcomes.

[25] The dummy variable for advanced academic degree can change from 0 to 1 over time if the teacher acquires an M.A. or Ph. D degree.

While the inclusion of schools' locality fixed effects helps reduce selection bias, complete elimination may not be achieved.[26] To further reduce the amount of selection effects, we employ a propensity score matching procedure to ensure that comparisons between students exposed to teachers with high versus low cognitive skills are made within similar groups of students (Imbens and Wooldridge, 2009). We define two additional binary variables indicating teachers' cognitive ability: whether the teacher has high or low cognitive skills based on their math matriculation scores and based on their psychometric math test scores (these variables equal one if the teacher's scores are at or above the median in each test).[27]

The identification strategy relies on the assumption that the counterfactuals of exposure to a high-ability teacher are students who are almost perfectly matched to those exposed to a low-ability teacher. Initially, we estimate the probability of being exposed to a high-cognitive-ability teacher (i.e., the propensity score) using probit regression, conditioned on the following covariates: students' characteristics, teachers' characteristics, school characteristics, socioeconomic cluster fixed effects, school district fixed effects, and subject and year fixed effects.

$$(2) \quad p_{ijklt} = Prob\left(A'_{nkt} = 1 \mid \beta_j, \gamma_t, \sigma_g, \vartheta_e, x_i, x_{kt}\right)$$

where the notation is the same as before, p_{ikljt} denotes the probability of student i being exposed to teacher k with a high cognitive ability measure, teaching subject j in school locality l and in year t; β_j is a subject fixed effect; γ_t is a year fixed effect; σ_g is the district fixed effects; ϑ_e is the socioeconomic cluster fixed effects; x_i is a vector of students' characteristics; x_{kt} is a vector of schools' and teachers' characteristics; and A'_{nkt} are the three teachers' cognitive ability dummies indicating teachers with high versus low cognitive ability.

For our main specification, we employed the propensity score nearest neighbor matching (NNM) procedure (Imbens and Wooldridge, 2009; Abadie and Imbens, 2011).[28]

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[26] The sensitivity of the results to the inclusion of students' characteristics in the main specification (Equations 1 and 2) is low. Nevertheless, the results of balancing tests indicate that there are still some correlations between several student and school characteristics and teachers' cognitive ability measures after controlling for locality fixed effects (about one-third of the covariates are significant).

[27] The teachers' academic degree variable is already a dummy variable (equals one if the teacher holds an M.A. degree or a Ph.D. degree).

[28] We use the standard specification of the three nearest neighbors with replacement. We estimate the standard error of the estimated treatment effect using a bootstrap resampling method of 500 replications, which permits estimation of the sampling variability of the estimated parameter.

Additionally, we present results using Kernel-based matching (KBM) as robustness tests for our matching procedure. The average treatment effect on the treated (ATT) is calculated as the average difference in students' outcomes between the treated units and their matched, weighted control units. In general, this can be expressed by the following equation:

$$(3)\ ATT = E\{E[y_{ijklt}|A'_{nkt} = 1, p_{ijklt}] - E[y_{ijklt}|A'_{nkt} = 0, p_{ijklt}]\}$$

Two important requirements should hold while using PSM analysis. The first requirement is the common support, which ensures there is sufficient overlap in the characteristics of treated and untreated units to find adequate matches. The second requirement is the balancing property, which requires similar distributions of covariates between the treatment and matched control groups.

The common support domain was employed as the primary criterion to assess the effectiveness of propensity score matching. Appendix Figure A1 shows that most observations fell within the common range of values for the short-term outcomes, resulting in minimal sample loss during the propensity score matching process. The balancing tests, also presented in Appendix Figure A1 for the short-term outcomes, indicate that propensity score matching reduced mean and median biases compared to before matching, thereby achieving improved balance between the treatment and control groups. Similar results were observed for long-term outcomes.[29]

4. Results

In this section, we analyze how science teachers' cognitive abilities affect their students' educational achievements. Initially, we investigate the short-term impact of teachers' cognitive abilities on students' performance in science matriculation exams at the end of high school. Subsequently, we assess their effect on students' longer-term educational outcomes six years post-high school.

4.1 Short-Term Effects on Educational Outcomes

Table 3 presents the estimated effects of teachers' cognitive ability measures on students' science matriculation test scores. The matriculation test scores in all four subjects (Biology, Physics, Chemistry, and Computer Science) are stacked together. We report

[29] The results of the common support and balancing tests for long-term outcomes are available from the authors upon request.

results of four specifications: the first is a simple OLS regression (Column 1); the second controls for locality, year, and subject fixed effects (Column 2); the third add teachers' characteristics (Column 3); and the last adds both teachers' and students' characteristics (Column 4). We estimate the impact of exposure to science teachers holding an advanced academic degree (M.A. or Ph.D.) (Row 1); the impact of teachers’ math matriculation test scores at the end of high school (Row 2); and the impact of teachers’ psychometric math scores (Row 3). Columns 5–8 present coefficients from a joint regression that includes all three measures of teachers' cognitive abilities for the four different specifications.

The simple OLS estimates in Rows 1–3 show significant impacts for all three measures of cognitive abilities, indicating that higher cognitive skills in teachers positively affect students' science test scores. The treatment measures remain robust when adding locality fixed effects. Adding teachers' characteristics changes the estimates of teachers' cognitive ability, rendering only the estimated effect of teachers' math matriculation test scores to be positive and statistically significant. These estimates show minimal change when further controlling for students’ characteristics, suggesting that teacher cognitive abilities are not strongly correlated with observed student characteristics once locality and other teacher characteristics are accounted for. In Columns 5–8 of Table 3, where all three cognitive ability measures are jointly included in the regression, the estimated effects exhibit a similar pattern to those in Columns 1–4, maintaining robustness to locality and teachers' characteristics and showing low collinearity between the measures.

Table 3
Teachers' Cognitive Ability Short-Term Effects on Students' Science Matriculation Test Scores

	Separate				Joint			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Advanced Academic Degree	0.21***	0.09*	0.047	0.038	0.159***	0.063	0.025	0.019
	(0.058)	(0.047)	(0.048)	(0.045)	(0.061)	(0.046)	(0.048)	(0.045)
Math Matriculation Test Score	0.085**	0.045	0.078**	0.078***	-0.026	0.049	0.076**	0.079**
	(0.037)	(0.032)	(0.032)	(0.028)	(0.043)	(0.035)	(0.036)	(0.033)
Psychometric Math Score	0.155***	0.005	0.018	0.018	0.15***	-0.022	-0.02	-0.019
	(0.030)	(0.029)	(0.031)	(0.029)	(0.037)	(0.033)	(0.035)	(0.033)
School Year FE		V	V	V		V	V	V
Matriculation Subject FE		V	V	V		V	V	V
School Locality FE		V	V	V		V	V	V
Teachers' Cha.			V	V			V	V
Students' Cha.				V				V
Observations					17,616	17,616	17,616	16,587

Notes: These regressions examine the short-term effects of teachers' cognitive abilities on students' science matriculation test scores. The dependent variable is the students' matriculation test scores in Biology, Physics, Chemistry, and Computer Science. The explanatory variables are our three measures of teachers' cognitive abilities: a dummy variable for the teacher holding an advanced academic degree (M.A. or Ph.D.) (Row 1); a continuous variable for the teacher's math matriculation test score at the end of high school (denoted in terms of standard deviations) (Row 2); and a continuous variable for the teacher's psychometric math score (denoted in terms of standard deviations) (Row 3). In Columns 1–4 the explanatory variables are included separately in the regression, while in Columns 5–8 they are included jointly in the same regression. Columns 1 and 5 are simple OLS regressions. Columns 2 and 6 add controls for the fixed effects of the school's locality, the school year, and the matriculation subject. Columns 3 and 7 add teachers' characteristics, and Columns 4 and 8 add also students' characteristics. Teachers' characteristics included are: age, gender, number of children, religiosity (Arab or Jew), new immigrant indicator, ethnicity indicators and an indicator for Jewish-religious school. Students' characteristics included are: gender, religiosity (Arab or Jew), number of siblings, father's years of schooling, mother's years of schooling, and ethnicity indicators. Standard errors are reported in parentheses and are clustered by teacher's ID. *** p<0.01, ** p<0.05, * p<0.1

The estimated effects of all three cognitive ability measures are mostly positive in the preferred specification (Table 3, Columns 4 and 8), but only the effect of teachers' math matriculation test scores is statistically significant and consistent in size at 0.08 (SE=0.03) across separated and joint regressions (Columns 4 and 8). In other words, being exposed to a teacher with the mean performances in math matriculation test scores compared to a teacher with a one standard deviation higher performances increases the students’ science test scores by 0.08 standard deviations, which amounts to an increase of about one point in students’ science test scores. This is not a very strong effect, considering other effect size interventions, but still has a meaningful economic significance. The effects of the other two cognitive skill measures—teachers’ academic degree and teachers’ psychometric math test scores—are positive but not statistically different from zero (0.04 (SE=0.045) and 0.018 (SE=0.03) respectively, according to the separated regression).[30,31]

The effect sizes we find in the short term, as described above—particularly those concerning teachers' math matriculation test scores at the end of high school—are quite consistent with what has been found in the relevant literature. We expand on this comparison to the literature in the following sections of the paper.

4.2 Long-Term Effect on Academic Outcomes

We tracked students from the end of high school through to post-secondary schooling, up to six years after high school. Table 4 presents evidence of the longer-term effects of teachers’ cognitive skills on several crucial educational outcomes. Panel A reports the estimated effect of teachers’ cognitive skills on the probability of pursuing post-secondary education; Panel B reports the estimated effect on the quality of post-secondary schooling (whether the institution is a research university); and Panel C reports the estimated effect on the orientation of post-secondary schooling (whether the major subject is one of the STEM subjects). We report estimates from regressions that include all three measures of

[30] These results are comparable to the results, presented in Appendix Table A3, of the binary variables of teachers' ability indicating whether the teacher has high or low cognitive skills according to their math matriculation and psychometric test scores (Column 1), for the separated preferred specification. The results from the preferred specification indicate that the estimated effect of being exposed to a teacher with higher-than-median math matriculation test scores compared to one with a lower grade is marginally significant (0.068, SE=0.044, P-value=0.124), while the estimated effect of being exposed to a teacher with higher-than-median psychometric math test scores compared to one with a lower grade is smaller and insignificant.

[31] Appendix Table A4 reports the respective coefficients and standard errors from a regression where the dependent variables are students’ raw test scores in science. The results are of similar effect sizes as in Table 3, and point to an increase of 0.85 in raw science tests scores as a result of an increase of one standard deviation in the math matriculation tests of science teachers.

cognitive skills separately (Columns 1–4) and jointly in the same regression (Columns 5–8).

Similar to Table 3, we present the estimated results in four specifications: the first is a simple OLS regression; the second adds controls for locality, years, and subject fixed effects; the third includes teachers' characteristics; and the fourth also includes students' characteristics. The estimates from both separated and joint regressions again show a consistent pattern when adding locality fixed effects and controlling for teachers' and students' characteristics, suggesting a low degree of collinearity between the three measures.

Importantly, many long-term outcomes are positive and statistically significant, indicating that the effects of teachers' cognitive skills persist through post-secondary schooling. Focusing on the preferred specification (Columns 4 and 8), which includes locality fixed effects and teachers' and students' characteristics, reveals that while teachers' cognitive abilities may not significantly impact the probability of pursuing post-secondary schooling, they do influence its quality and orientation.[32] Specifically, the most influential cognitive skill of teachers is their math knowledge measure, which affects both long-term outcomes, according to both separated and joint regressions. Teachers' math knowledge measure increases the probability of attending a research university and studying a STEM major subject. The estimated effects of teachers' math matriculation test scores are both positive and statistically significant for these outcomes (0.051, SE=0.02 and 0.041, SE=0.01 according to the separated regression). Teachers' academic degrees increase the probability of students studying a STEM major subject (0.33, SE=0.02 according to the separated regression). The estimated effects of teachers' psychometric math test scores are also significant, though only when the three cognitive measures of teachers are not jointly included in one regression (0.031, SE=0.02 and 0.026, SE=0.01).[33,34]

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[32] Only teachers' Psychometric math test scores have a marginal effect on the probability of pursuing post-secondary schooling (0.026, SE=0.015, P-value= 0.09 according to the separated regression), but this effect does not persist in the joint regression.

[33] Appendix Table A5 reports the respective coefficients and standard errors from a Probit regression. The marginal effects at the means (in italics) resemble the coefficients of the linear probability regression in Table 4.

[34] Due to the 'Significant Learning' reform, which changed the minimum matriculation requirements, we have restricted our sample to students who took an advanced-level science matriculation exam, rather than including all students who took any level of science matriculation exams. The results of relaxing this restriction are presented in Appendix Table A6. Appendix Table A6 shows the estimated effect of teachers' cognitive skills on the entire population of students who took all levels of science matriculation exams. with somewhat larger effect sizes on almost all short- and long-term outcomes.

Table 4
Teachers' Cognitive Ability Long-Term Effects on Students' Academic Outcomes

	Separate				Joint			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Post-Secondary Education				
Advanced Academic Degree	0.056*	-0.020	-0.028	-0.024	0.040	-0.008	-0.019	-0.013
	(0.033)	(0.033)	(0.032)	(0.028)	(0.032)	(0.034)	(0.033)	(0.031)
Math Matriculation Test Score	0.082***	0.018	0.017	0.018	0.038*	0.009	0.001	0.004
	(0.019)	(0.019)	(0.021)	(0.018)	(0.021)	(0.019)	(0.023)	(0.021)
Psychometric Math Score	0.094***	0.030*	0.033**	0.026*	0.067***	0.028*	0.036*	0.025
	(0.016)	(0.016)	(0.017)	(0.015)	(0.020)	(0.016)	(0.019)	(0.018)
				Panel B. Quality of Post-Secondary Education				
Advanced Academic Degree	0.066**	-0.003	0.003	0.008	0.026	-0.003	0.004	0.010
	(0.032)	(0.026)	(0.027)	(0.027)	(0.031)	(0.026)	(0.028)	(0.028)
Math Matriculation Test Score	0.089***	0.05***	0.051**	0.051**	0.029*	0.047***	0.043**	0.048**
	(0.016)	(0.018)	(0.021)	(0.021)	(0.018)	(0.017)	(0.021)	(0.021)
Psychometric Math Score	0.105***	0.036**	0.038**	0.031*	0.084***	0.017	0.018	0.008
	(0.012)	(0.016)	(0.018)	(0.018)	(0.015)	(0.015)	(0.018)	(0.018)
				Panel C. Orientation of Post-Secondary Education				
Advanced Academic Degree	0.062**	0.026	0.028	0.033*	0.038	0.032*	0.036*	0.041**
	(0.028)	(0.019)	(0.018)	(0.018)	(0.025)	(0.019)	(0.019)	(0.019)
Math Matriculation Test Score	0.085***	0.051***	0.04***	0.041***	0.039**	0.043**	0.024	0.030*
	(0.014)	(0.015)	(0.015)	(0.014)	(0.016)	(0.017)	(0.018)	(0.017)
Psychometric Math Score	0.093***	0.031***	0.03**	0.026*	0.062***	0.013	0.019	0.012
	(0.011)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.015)	(0.014)
School Year FE		V	V	V		V	V	V
Matriculation Subject FE		V	V	V		V	V	V
School Locality FE		V	V	V		V	V	V
Teachers' Cha.			V	V			V	V
Students' Cha.				V				V
Observations					5,750	5,750	5,750	5,439

Notes: These regressions examine the long-term effects of teachers' cognitive abilities on students' academic outcomes. The dependent variables are: the probability of our sample students pursuing post-secondary education up to six years after the end of high school (Panel A); the probability of pursuing post-secondary education at a research university (Panel B); and the probability of pursuing post-secondary education in STEM major subjects (Mathematics, Statistics, Biology, Engineering, and Medicine) (Panel C). Tracking the students for no more than six years after high school compelled us to keep only the sample years 2012–2014, thus reducing the number of observations in these regressions. The explanatory variables are the same as in Table 3. In Columns 1–4, the explanatory variables are included separately in the regression, while in Columns 5–8, they are included jointly in the same regression. Columns 1 and 5 are simple OLS regressions. Columns 2 and 6 add controls for the fixed effects of the school's locality, the school year, and the matriculation subject. Columns 3 and 7 add teachers' characteristics, and Columns 4 and 8 also add students' characteristics. Teachers' and students' characteristics included are the same as in Table 3. The number of observations varies slightly across the separate regressions in Columns 1–4 but is not lower than the number of observations in the corresponding joint regression from Columns 5–8. Standard errors are reported in parentheses and are clustered by teacher's ID. *** p<0.01, ** p<0.05, * p<0.1

The interpretation of these results indicates that teachers' cognitive skills have significant and rather far-reaching effects on long-term outcomes. Exposure to a teacher with advanced academic qualifications, such as an M.A. or Ph.D. degree, compared to a teacher with lower academic qualifications, increases the probability of studying a STEM major subject by 3.3 percentage points. Moreover, exposure to a teacher whose math matriculation test scores are one standard deviation above the mean, compared to a teacher with mean performance, enhances both the quality and orientation of post-secondary schooling. It increases the probability of studying at a research university by 5.1 percentage points and the probability of choosing a STEM major subject by 4.1 percentage points. Similarly, exposure to teachers whose psychometric scores are one standard deviation above than the mean, compared to a teacher with mean performance, increases these long-term outcomes by 3.1 and 2.6 percentage points, respectively, but these effects are only significant according to the separated regressions.[35]

4.3 Comparing the Results to the Literature

The existing literature consistently identifies various measures of teachers' cognitive abilities and their impact on student achievement. These measures often focus on skills that can be classified as either more acquired general-oriented skills or more innate math-specific oriented skills. Innate abilities are typically reflected in teachers' scores on psychometric tests, college entrance exams, and licensing exams, while acquired abilities encompass factors like years of experience and academic background. Research generally indicates that the relationship between teachers' innate cognitive skills and student achievement growth tends to be more robust.

For instance, studies find that an increase of one standard deviation in teachers' licensing test scores is associated with increases in student math scores, ranging from 0.012 standard deviations among 5th-grade students (Clotfelter et al., 2006) to 0.033 standard deviations among middle school students (Goldhaber et al., 2017), and increases of 0.047 and 0.016 standard deviations in math and biology subjects, respectively, among high school students (Clotfelter et al., 2010). Clotfelter et al. (2010) further reveal that certification in the subject

[35] These findings align closely with those in Appendix Table A3, which presents the effects using binary variables of teachers' ability in the preferred specification. The results are statistically significant primarily for the quality and orientation of post-secondary schooling. Exposure to a teacher with higher than median math matriculation test scores compared to one with a lower score increases these outcomes by 5.6 and 3.8 percentage points, respectively. Conversely, exposure to teachers with higher than median psychometric math test score compared to one with a lower score does not show statistically significant differences from zero in these long-term outcomes.

taught has a stronger positive effect on students' end-of-course test scores (0.07 standard deviations) compared to certification in a related subject (0.05 standard deviations). Overall, the size of our short-term estimate of the effect of teachers' math matriculation test scores is marginally higher than found in the literature (0.08, SE=0.03). This is not a very strong effect, considering the effect sizes of other interventions, but still has a meaningful economic significance.

In contrast, evidence regarding general acquired knowledge and broader experience such as academic background and years of experience is more mixed. While many studies do not find a strong relationship between stronger academic backgrounds and large performance gains for students, years of teaching experience consistently show positive correlations with students' educational outcomes. For example, Clotfelter et al. (2010) found that having a graduate degree (M.A. or Ph.D.) had no greater association with end-of-course test scores than not having one, whereas years of experience were positively linked with improved teaching outcomes.[36] Our results highlight the importance of teachers' math matriculation scores compared to other cognitive skills for both short- and long-term educational outcomes[37], especially the consistent effect of teachers' math matriculation test scores at the end of high school, which is similarly found in the literature in terms of effect size in the short-term. Several long-term educational outcomes appear to be influenced to some extent by teachers' additional cognitive skills. To the best of our knowledge, existing literature predominantly focuses on the short-term effects of teacher quality on student outcomes, providing limited comparable results for long-term outcomes. However, the fact that our long-term results are as robust as the short-term ones suggests underlying mechanisms through which teachers' cognitive skills affect their students.

The literature proposes two main general pathways through which teachers with higher cognitive skills generate larger achievement gains. One category of explanations involves what could be termed "active" teacher effects, where teachers' interactions with students

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[36] Although our sample consists of relatively young teachers, the estimated effect of one year of experience in our preferred specification regression is positive and significant (0.023, SE=0.008). This result is comparable in effect size to findings in the literature, where having 21-27 years of experience, compared to no experience at all, is associated with an increase of 0.09 standard deviations in 5th-grade students' scores in math and reading (Clotfelter et al., 2006), and an increase of 0.063 standard deviations in end-of-course tests for high school students (Clotfelter et al., 2010).

[37] We assume that the psychometric math scores represent somewhat more innate mathematics- oriented abilities than our advanced academic science degree measure. Most of the economic literature refers to this kind of intelligence test as measuring more innate than acquired skills, though few recent papers emphasize that the line between innate and acquired abilities is often blurred, and that any test can be influenced by multiple factors (e.g. Jacob and Rothstein, 2016; Friedman-Sokuler and Justman, 2024).

and explicit teaching behaviors enhance student learning and achievements. Teachers with higher cognitive skills are presumed to be more effective in teaching complex subjects and in creating conducive learning environments (Rockoff, 2004; Rivkin and Hanushek, 2005).

A second category of explanations points to "passive" teacher effects, where these effects are simply triggered by a teacher's attributes rather than explicit behaviors. Examples include 'role-model' or stereotype threat effects, where the presence of certain teacher attributes enhances students' academic motivation and expectations (Bettinger and Long, 2005; Gershenson et al., 2022).

Our findings, indicating that teachers' cognitive skills have significant effects in both the short- and long-run, suggest that both of these underlying mechanisms may be at play. Teachers' cognitive skills likely have a direct short-term impact on student performance through more effective teaching practices, as well as a long-term impact through the 'role-model' channel, enhancing students' motivation and their inclination to pursue post-secondary studies in STEM subjects.

4.4 Results from an Alternative Estimation Strategy

We present the results from two propensity score matching procedures: Kernel-based matching and nearest neighbor matching. Table 5 reports the estimated effects of the three measures of teachers' cognitive abilities on both short- and long-term educational outcomes: students' science matriculation test scores (Columns 1 and 2); the probability of pursuing post-secondary education up to six years after the end of high school (Columns 3 and 4); the quality of post-secondary schooling (whether the institution is a research university) (Columns 5 and 6); and the orientation of post-secondary schooling (whether the major subject is a STEM subject) (Columns 7 and 8). We report estimates from regressions that include the three measures of cognitive skills separately, controlling for year, subject, geographic area, socioeconomic clusters fixed effects, and additional controls for teachers' and students' characteristics.[38]

[38] We do not include all three measures of cognitive skills jointly in a regression due to the propensity score matching procedure that, by construction, enables just one treated and untreated group for each cognitive skills measurement.

Table 5

Short- and Long-Term Effects of Teachers' Cognitive Ability on Students' Academic Outcomes from a PSM Analysis

	Science Matriculation Test Score		**Post-Secondary Education**		**Quality of Post-Secondary Education**		**Orientation of Post-Secondary Education**	
	KBM	**NNM**	**KBM**	**NNM**	**KBM**	**NNM**	**KBM**	**NNM**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Advanced Academic Degree	0.066***	0.064***	0.022	0.020	0.018	0.019	0.012	0.000
	(0.018)	(0.023)	(0.019)	(0.025)	(0.016)	(0.023)	(0.015)	(0.023)
Math Matriculation Test Score	0.077***	0.061***	0.015	0.034	0.102***	0.107***	0.047**	0.073***
I(x) = [x > med{X}]	(0.022)	(0.027)	(0.034)	(0.029)	(0.025)	(0.028)	(0.022)	(0.026)
Psychometric Math Score	0.107***	0.099***	0.005	0.010	0.005	0.027	0.066***	0.047**
I(x) = [x > med{X}]	(0.028)	(0.037)	(0.030)	(0.027)	(0.023)	(0.026)	(0.022)	(0.023)
School Year FE	V	V	V	V	V	V	V	V
Matriculation Subject FE	V	V	V	V	V	V	V	V
Locality District FE	V	V	V	V	V	V	V	V
Locality Socio-Economic Cluster FE	V	V	V	V	V	V	V	V
Teacher's Cha.	V	V	V	V	V	V	V	V
Student's Cha.	V	V	V	V	V	V	V	V
Common Support Imposed	Yes		Yes		Yes		Yes	

Notes: This table presents the main results from the propensity score matching (PSM) analysis. We employ two matching methods—kernel-based matching (KBM), and nearest-neighbors matching (NNM) with 3 nearest neighbors. Due to cost-effectiveness considerations, we bootstrap the analysis (500 replications) only for the NNM specifications, and report the bootstrapped standard errors for those specifications only (even-numbered columns). The short-term dependent variable is as in Table 3—the students' matriculation test scores (Columns 1–2). The long-term dependent variables are as in Table 4: our sample students' probability of pursuing post-secondary education up to six years after the end of high school (Columns 3–4); the probability of pursuing post-secondary education at a research university (Columns 5–6); and the probability of pursuing post-secondary education in STEM major subjects (Columns 7–8). The explanatory variables are our three measures of teachers' cognitive abilities as in Tables 3 and 4, while the continuous variables for the teacher's math matriculation test and psychometric math scores are now dummies that equal 1 if teacher's score equals the median score value or above among the sample teachers, and 0 if below the median value (Rows 2 and 3). In all columns the explanatory variables enter the analysis separately and include controls for the fixed effects of the school locality's district, the school locality's socioeconomic cluster, the school year, and the matriculation subject, as well as teachers' and students' characteristics. The teachers' and students' characteristics included are the same as in Tables 3 and 4. Finally, the common support is imposed in all specifications. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In Columns 1 and 2, we present the results for short-term effects. All three measures of teachers' cognitive skills show positive and statistically significant effects (results are presented for the Kernel-based matching): exposure to a teacher with an advanced academic degree (0.066, SE=0.018), exposure to a teacher with higher-than-median math matriculation test scores (0.077, SE=0.022), and exposure to a teacher with higher-than-median psychometric math scores (0.084, SE=0.025). Similar results are found with nearest neighbor matching. These effect sizes are somewhat larger and all of them are significant compared to the fixed effects strategy, noting especially the effect of the teachers' psychometric math score measure, which is practically zero according the latter (comparing the results to those of the binary representation of the cognitive skill measures of teachers reported in Appendix Table A3: 0.066, SE=0.018 compared to 0.038, SE=0.045 for the academic degree measure, 0.077, SE=0.022 compared to 0.068, SE=0.044 for the math matriculation score measure, and 0.107 SE=0.028 compared to 0.009 SE=0.05 for the psychometric math score measure, respectively).

Columns 3 to 8 present the long-term effects of the three skill measures. The estimated effects on the probability of pursuing post-secondary education are small and not significant in both PSM and fixed effects estimation strategies. However, for the quality and orientation of post-secondary schooling, teachers' math matriculation test scores appear most influential according to this estimation strategy as well. These results align closely with those from the fixed effects strategy (Appendix Table A3), though effect sizes are again larger in the PSM estimation strategy (0.102, SE=0.025 compared to 0.056, SE=0.026 for quality, and 0.047, SE=0.022 compared to 0.038, SE=0.021 for orientation in PSM and FE strategies, respectively). The estimated effects of the teachers' academic degree measure on the orientation of education pursued are not significant, as in the FE strategy, but the estimated effects of teachers' psychometric math test scores are significantly different from zero (0.066, SE=0.022 compared to 0.009, SE=0.024, respectively).

As noted above, the use of PSM allows us to compare students who are very similar in their observable characteristics, while the use of Locality FE enables us to control for unobservable characteristics at the school locality level. The consistency in the results obtained from both methods serves as an additional robustness test for the main specification and strengthens the hypothesis that any potential bias from endogeneity due to unobservable characteristics, as well as from the sorting of students to teachers, is limited.

4.5 Robustness tests

As discussed in the literature on the impact of teachers' attributes on students' educational outcomes, concerns arise regarding the sorting of students to teachers and schools, which complicates identifying causal relationships. Teachers with stronger qualifications often teach more affluent students, a phenomenon that may occur not only within localities but also within schools and classes. In our study, students may be sorted not only to schools but also to subjects based on teachers' qualifications.

Thus far, the robustness of our results to the inclusion of students' characteristics in regressions controlling for localities fixed effects suggests minimal correlation between teachers' cognitive skill measures and students' observed characteristics within localities. Additionally, our findings align between fixed effects and propensity score matching (PSM) strategies, where PSM matches students based on observables to test differences in outcomes between those assigned to teachers with higher versus lower cognitive skills.

We now provide further sensitivity tests to support our identification strategies. First, results remain robust when controlling for students' previous achievements, i.e. GEMS scores from earlier grades (8th and 5th grades). Second, to assess the extent to which the sorting of more affluent students to teachers with stronger qualifications might affect the results, we control for several school-level quality measures. Third, to address the concern that students may select advanced-level courses based on their teacher's qualifications, we demonstrate that higher cognitive skills of teachers do not increase the probability of students choosing to study the subject. Finally, we also consider the argument that variations in class attributes, which affect the learning environment, within localities and over time, might potentially confound our results.

The estimated effects of the three measures of teacher cognitive skills on short- and long-term educational outcomes, according to the preferred specification while additionally controlling for students' previous GEMS test scores[39], are presented in Appendix Table A7. Importantly, the estimated effects, which were positive and significant in Tables 3 and 4, remain largely significant after accounting for previous

[39] We do not control for students' GEMS scores in the main specification in order to maintain as large a sample as possible, as these data are missing for about 18% of our observations.

grades, with only marginally lower effect sizes. In the short term, the estimated effect of teachers' math matriculation scores decreases slightly and continues to be the only significant cognitive skill measure (0.054, SE=0.028, compared to 0.078, SE=0.028). The robustness of the results is also evident at later educational stages, where the teachers' math matriculation test scores measure is dominant (0.044, SE=0.02 compared to 0.051, SE=0.021 for the quality outcome; 0.043, SE=0.013 compared to 0.041, SE=0.014 for the orientation outcome). The effect of the teachers' academic degree measure on the orientation of education pursued ceased to be significant, though the estimated effects of teachers' psychometric math test scores remain the same as in Table 4 (0.026, SE=0.012).

Additionally, results from both propensity score matching procedures (Appendix Table A8) show also robustness to the inclusion of students' previous GEMS test scores, further suggesting limited omitted variable bias due to correlations between students' unobserved characteristics and teachers' cognitive skill measures.

Controlling for several school-level quality measures in the preferred specification, such as the school quality of teachers (the proportion of teachers with advanced academic degrees at school) and the school parental earning (or students' average parental schooling), the estimated effects of the three measures of teacher cognitive skills on short- and long-term educational outcomes are presented in Appendix Tables A9 and A10, respectively. As reported, the estimated effects are very similar to those in Tables 3 and 4. The only notable difference is that the estimated effects of teachers' math matriculation scores in the short term are slightly lower when controlling for students' average family income, though still statistically significant (0.055, SE=0.03, compared to 0.078, SE=0.028 in Table 3). If we replacing students' average family income with students' average parental schooling as controls, we obtain practically identical results, supporting the view that the sorting of students into better schools and its potential impact on the results is minimal.

Addressing concerns that students might choose advanced-level subjects based on teachers' qualifications, Appendix Table A11 examines the correlation between students' probability of taking an advanced science matriculation course and their teachers' cognitive skills.[40] Results from all four specifications, OLS regressions and subsequent

[40] As a robustness check, since we do not have the students' admission rates to advanced-level courses, only data on those who took the exam or part of its units, we also test the correlation between teachers' cognitive skills and students' probability of taking the final exam at any number of units as a proxy for admission rates. Appendix Table A12, which presents the estimated effects on students' probability of taking a science matriculation course at any level from similar specifications, indicates that all estimates are not significantly different from zero.

regressions controlling for locality, years, subjects fixed effects, teachers’ characteristics, and students’ characteristics show no significant correlation between teachers’ cognitive skills and students’ probability of taking advanced-level courses. This suggests that teachers' cognitive abilities are not a determining factor in students' decisions regarding advanced-level subject choices in high school, but are reflected in their students' test performances and long-term educational outcomes.

Finally, Appendix Table A13 and Appendix Table A14 report results from the preferred specification controlling for two confounding variables related to the learning environment: class size and teaching hours (measured as full-time equivalents (FTE)). These variables vary within and between localities due to budgeting rules[41], criteria for STEM funding[42], and science teacher availability per locality.[43] Reforms such as the technological-scientific reserve program and the national program for strengthening mathematics studies may also influence these variables over time. Despite potential correlations with teachers’ credentials and educational outcomes, estimated effects of teachers’ cognitive ability measures on short- and long-term outcomes, while controlling for these variables, are only marginally different from those reported in Tables 3 and 4. This consistency further supports our identification strategy.

4.6 Heterogeneous Treatment Effects of Teachers’ Cognitive Skill Measures

To gain further insight into the effects of teachers' cognitive skills on students’ academic success, we explore heterogeneous effects across several dimensions. In Table 6 and Table 7, we present the estimated effects of teachers’ cognitive skills on test scores for different student and school characteristics, based on the interaction of each teacher's cognitive skill measure with each student and school characteristic.[44] We focus on short-term educational outcomes, i.e. students’ science matriculation test scores. The estimates for the

[41] For more details about the budgeting rules by which teaching hours are allocated see Ministry of Education and Ministry of Finance 2014: reports of the interministerial team on narrowing disparity in education-system budgeting:
https://meyda.education.gov.il/files/MinhalCalcala/Doh_benmisradi_zimzumpearim.pdf

[42] For example, see the report on the criteria for school funding for physics and math studies in high schools: gaps in the teaching of physics subjects and mathematics in selected aspects (Knesset Research and Information Center (2022)) (in Hebrew).

[43] School principals' reports on teacher shortages vary across geographic locations and different nurture index levels (Knesset Research and Information Center (2023): Teacher Shortage - A Review) https://fs.knesset.gov.il/globaldocs/MMM/09f3dfaf-607c-ed11-8150-005056aac6c3/2_09f3dfaf-607c-ed11-8150-005056aac6c3_11_19858.pdf (in Hebrew).

[44] Estimating the equation separately for each population subset yields almost identical results to those obtained from a single regression that includes interactions between the cognitive skills measures and the gender of the student/teacher.

specification where the three measures of teachers' cognitive abilities are included separately in three regressions are shown.[45] We use the preferred specification, which includes year, subject, and locality fixed effects, as well as teachers' and students' characteristics.

Columns 1 and 2 of Table 6 report the estimated effects by students' previous GEMS scores, higher or lower than the median of our sample students. Columns 3 and 4 report the estimated effects by the school's geographical location, central versus peripheral. Columns 5 and 6 report the estimated effects by the school locality's socioeconomic cluster, higher or lower than the median of our sample schools. Columns 7 and 8 report the estimated effects by school ethnicity, Jewish schools versus Arab schools. Columns 9 and 10 report the estimated effects by school religiosity, Jewish secular versus religious schools.

Empirical evidence suggests that students with stronger aptitude benefit more from improved teacher credentials. Regarding students' socioeconomic background, the evidence is more mixed and depends on students' educational stage. According to the literature, there may be several explanations for this. For instance, teachers with higher cognitive skills leverage greater resources more effectively to enhance learning outcomes (Chetty et al. 2014), and use advanced teaching methods, benefiting students who are already performing well and are better prepared (Hanushek and Rivkin 2012). Clotfelter et al. (2006) documented that teachers with stronger math credentials generate larger achievement gains among relatively advantaged students. Similarly, Grönqvist & Vlachos (2016) found that the effect of teachers' cognitive abilities is greater on higher aptitude students (measured by GPA) than on their lower aptitude counterparts. Bientenbeck et al. (2016) showed that the effects of teachers' subject-specific knowledge are smaller for students without access to textbooks and from schools with poorer facilities. Nevertheless, other studies have used teacher value-added models to show that teacher quality in early educational stages is particularly important for students with lower aptitude (Aaronson, Barrow, and Sander, 2007; USDoE, 2013).

We find similar patterns of heterogeneous effects of teachers' cognitive abilities across students' previous achievements. According to Columns 1–2, the estimated effects for most measures of teachers' cognitive skills are higher among students with better previous

[45] The results of the specification where the three measures of teachers' cognitive abilities are included jointly in the same regression are similar and are available from the authors upon request.

GEMS scores. The estimated effect of teachers' matriculation test scores is statistically stronger for high-performing students than for their counterparts (0.087, SE=0.03, and 0.021, SE=0.006, respectively, p-value=0.02). However, heterogeneous effects across geographic areas and schools' socioeconomic cluster are not statistically different across groups according to Columns 3–4 and 5–6 respectively. The estimated effect of teachers' matriculation test scores benefits students from the periphery marginally more than counterparts (0.088, SE=0.04, and 0.066, SE=0.04, respectively), as well as students from schools in high socioeconomic clusters (0.094, SE=0.04, and 0.058, SE=0.04, respectively).[46]

[46] Using alternative definitions for high versus low aptitude and high versus low socioeconomic clusters—such as referencing the median of all students and schools instead of the sample medians—does not affect the results. Similarly, redefining central versus peripheral geographic areas. The only exception is when excluding only the Haifa district, which strengthens the statistical significance of the estimated effect of teachers' academic degrees, making it marginally more pronounced for students in centrally located schools (including only Central District, Tel Aviv District and Jerusalem District) compared to those in peripheral areas.

Table 6

Short-Term Effects of Teachers' Cognitive Ability on Students' Science Matriculation Test Scores, by Subgroups of Students and Schools

	Student Aptitude		School Area		School Locality Socioeconomic Cluster		Student Sector		Jewish School Religiosity	
	High Aptitude	Low Aptitude	Center	Periphery	High Cluster	Low Cluster	Arabs	Jews	Religious	Secular
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Advanced Academic Degree	0.015	-0.019	0.039	0.038	0.028	0.058	0.075	-0.024	-0.052	-0.057
	(0.05)	(0.06)	(0.08)	(0.05)	(0.05)	(0.08)	(0.06)	(0.06)	(0.07)	(0.08)
Math Matriculation Test Score	0.087***	0.021	0.066*	0.088**	0.094***	0.058	0.084**	0.067	0.115**	0.082*
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.06)	(0.04)
Psychometric Math Score	-0.002	0.006	0.006	0.026	0.022	0.019	0.026	-0.001	0.064	0.047
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)	(0.04)
School Year FE	V	V	V	V	V	V	V	V	V	V
Matriculation Subject FE	V	V	V	V	V	V	V	V	V	V
School Locality FE	V	V	V	V	V	V	V	V	V	V
Teachers' Cha.	V	V	V	V	V	V	V	V	V	V
Students' Cha.	V	V	V	V	V	V	V	V	V	V

Notes: These regressions examine the heterogenous short-term effects of teachers' cognitive abilities on students' matriculation test scores, over different subgroups of students. The dependent variable is the students' matriculation test scores in Biology, Physics, Chemistry, and Computer Science, and the explanatory variables are the same as in Tables 3 and 4. Columns 1–2 report the effect of each explanatory variable by student aptitude (high aptitude is defined as the median GEMS previous score or higher among the sample); Columns 3–4 report the effects by the schools' geographic area (periphery and center); Columns 5–6 report the effects by school socioeconomic background according to the socioeconomic cluster rank of the school's locality (high cluster is defined as the median cluster or higher); Columns 7–8 report the effects by the students' sector (Arabs and Jews); and Columns 9–10 report the effects by school religiosity (religious and secular), among the Jewish school observations only. In all columns the explanatory variables enter the analysis separately and include controls for the fixed effects of the school's locality, the school year, and the matriculation subject, as well as teachers' and students' characteristics. The teachers' and students' characteristics included are the same as in Tables 3 and 4. Standard errors are reported in parentheses and are clustered by teacher's ID. *** p<0.01, ** p<0.05, * p<0.1

We also consider the heterogeneous treatment effects of teachers' cognitive skills based on the school's religious and ethnic background. We postulate that children from minority groups might suffer from fewer resources and less school funding, and might be less competent, although in the case of religious Jewish schools, resources are higher than those of secular Jewish schools.[47] However, results presented in Columns 7–8 and 9–10 reveal similar effects across school religious and ethnic backgrounds. As in Table 3, the only cognitive skill measure of teachers that is significantly different from zero is teachers' math matriculation test scores. Columns 7 and 8 show that teachers' math matriculation test scores exhibit significant positive effects for both Jewish and Arab sectors, with slightly larger effect size in the Arab sector than in the Jewish sector: 0.084 (SE=0.03) compared to 0.067 (SE=0.04), respectively, though the difference is not statistically significant. In the Jewish sector, Columns 9 and 10 show that teachers' math matriculation test scores have a stronger effect on religious Jewish students than on secular Jewish students: 0.115 (SE=0.06), compared to 0.082, (SE=0.04), respectively.

Finally, we test the heterogeneous effects across gender. The evidence in the literature mostly concludes that the effect of teachers' cognitive ability on student achievement appears to be highly asymmetric, both between male and female students (with males being more affected) and between male and female teachers (with stronger positive effects from male teachers) (Aaronson et al. 2007; Hanushek and Rivkin 2006). Some studies even suggest this asymmetry might be rooted in student-teacher gender match characteristics. For example, Metzler and Woessmann (2012) and Grönqvist and Vlachos (2015) find that the effect of teachers' cognitive skills is stronger on their same-gender students than on students of the opposite gender.

Table 7 tests the heterogeneous effects across the genders of students and teachers and their interaction. Columns 1 and 2 present the heterogeneous effect across the gender of the students by interacting each measure of teachers' cognitive skills with the student's gender. Columns 3 and 4 present the heterogeneous effect across the gender of the teachers by interacting each measure of teachers' cognitive skills with the teacher's gender. Columns 5 and 6 report the heterogeneous effect across both groups' gender by double-interacting each measure of teachers' cognitive skills with the gender of the student and

[47] For further information about the budgeting rules governing the allocation of teaching hours, refer to the Ministry of Education and Ministry of Finance (2014) report on narrowing disparities in education system budgeting. Part of the budgetary gap stems from unique components provided exclusively in state-religious schools, aimed at funding items such as additional prayer hours and enrichment in Israeli culture studies (Bank of Israel 2022a)

the gender of the teacher. We present the estimates of teachers' cognitive skills focusing on short-term educational outcomes, i.e. students' science matriculation test scores, for the first specification, where the three measures of teachers' cognitive abilities are included separately in three regressions. We use the preferred specification, which includes year, subject, and locality fixed effects as well as teachers' and students' characteristics.

Columns 1–2 and 3–4 reveal that various measures of cognitive skills have contrasting effects across the genders of students and teachers. Female students are statistically more affected by their teachers' academic degrees, although the effect is not statistically significant (0.061, SE=0.05, compared to -0.002, SE=0.05, p-value=0.1), with female teachers in this measure having a statistically stronger positive effects on students than to their male counterparts (0.118, SE=0.05, compared to -0.158, SE=0.08, p-value=0.001).

Surprisingly, math matriculation and psychometric math test scores exhibit opposite effects. Male students are statistically more affected by their teachers' math performance (0.105, SE=0.03, compared to 0.063, SE=0.03, p-value=0.1, for math matriculation test scores). Male teachers' psychometric math test performance has a stronger impact on their students than their female counterparts, although the differences are not statistically significant.[48]

[48] The number of observations corresponding to the results of the subpopulation reported in Table 7 are: 8401 in Column 5; 4325 in Column 6; 2857 in Column 7; and 2528 in Column 8.

Table 7

Short-Term Effects of Teachers' Cognitive Ability on Students' Science Matriculation Test Scores, by Students' and Teachers' Gender Matching

	Female Students	Male Students	Female Teachers	Male Teachers	Female Teachers		Male Teachers	
					Female Students	Male Students	Female Students	Male Students
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Advanced Academic Degree	0.061	-0.002	0.118**	-0.158*	0.131***	0.093	-0.146	-0.171*
	(0.05)	(0.05)	(0.05)	(0.08)	(0.05)	(0.06)	(0.09)	(0.09)
Math Matriculation Test Score	0.063**	0.105***	0.061*	0.113**	0.052	0.077**	0.082	0.145***
	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)	(0.04)	(0.06)	(0.05)
Psychometric Math Score	-0.005	0.064**	0.000	0.050	-0.002	0.009	-0.012	0.135***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
School Year FE	V	V	V	V	V	V	V	V
Matriculation Subject FE	V	V	V	V	V	V	V	V
School Locality FE	V	V	V	V	V	V	V	V
Teachers' Cha.	V	V	V	V	V	V	V	V
Students' Cha.	V	V	V	V	V	V	V	V

Notes: These regressions examine the heterogenous short-term effects of teachers' cognitive abilities on students' matriculation test scores, by the gender of students and teachers and their interaction. The dependent variable is the students' matriculation test scores in Biology, Physics, Chemistry, and Computer Science, and the explanatory variables are the same as in Tables 3 and 4. Columns 1–2 report the effect of each explanatory variable by the gender of the students; Columns 3–4 report the effects by the gender of the teachers; Columns 5–6 report the effect of each explanatory variable by student gender when the teacher is female. Columns 7–8 report the same but when the teacher is male. In all columns the explanatory variables enter the analysis separately and include controls for the fixed effects of the school's locality, the school year, and the matriculation subject, as well as teachers' and students' characteristics. The teachers' and students' characteristics included are the same as in Tables 3 and 4. Standard errors are reported in parentheses and are clustered by teacher's ID. *** p<0.01, ** p<0.05, * p<0.1

These patterns across both teachers' gender and students' gender raise the question of whether the resemblance results from teacher-student gender match. Indeed, the results in columns 5–6 show that teachers' academic degrees have a statistically stronger positive impact on their student if the teacher is a female teacher, especially among female students (0.131 SE=0.05 among female teachers compared to -0.104 SE=0.09 among male teachers). The opposite is found for teachers' math matriculation and psychometric math test scores, which have a stronger impact on boys, especially if the teacher is male (0.135 SE=0.04 among male teachers compared to 0.009 SE=0.04 among female teachers, for psychometric math test scores).

The considerable importance of the gender match between teachers and students in the impact of cognitive abilities on student achievements, which manifests differently across genders—female students benefit more from their female teachers' advanced academic degrees, while male students benefit more from their male teachers' achievements in mathematics and the quantitative psychometric tests—can be explained by the two aforementioned channels through which teachers influence educational outcomes. Female teachers with advanced degrees might serve as role models for girls, encouraging them, raising their motivation, and lowering the "stereotype threat" (the "passive" teacher effects channel). The fact that teachers' math matriculation and psychometric test scores are not directly observed credentials suggests that the effect of these credentials might be derived from the "active" teacher effects channel. Teachers with high cognitive ability are said to employ teaching methods that create a more rigorous and competitive learning environment, which might deter female students (Hanushek and Rivkin 2006; Niederle and Vesterlund 2007). We postulate that this might explain why teachers' high math matriculation and psychometric test scores have a stronger effect on male students.

5. Conclusion

In this study, we examined the impact of teachers' cognitive abilities on their students' short- and long-term academic achievements. Utilizing detailed administrative data spanning the years 2012 to 2019, we identified Israeli 12th-grade students and their science teachers, constructing three proxies for teachers' cognitive abilities: holding an advanced academic degree, math matriculation test scores, and psychometric math scores. Focusing on students and teachers of STEM subjects (i.e., Biology, Chemistry, Physics, and

Computer Science), we employed both school-locality fixed effects and propensity score matching identification strategies.

The analysis underscores the relative importance of teachers' math matriculation scores compared to other cognitive skills on students' short-term science matriculation scores and long-term educational outcomes. In the long term, all three cognitive measures significantly influence both the quality and orientation of post-secondary education attained. However, teachers' specific math-oriented skills, as represented by their math matriculation scores, consistently exhibit the strongest effect. These findings suggest that the benefits of having cognitively skilled teachers extend well beyond high school, indicating that teacher influence emerges not only from direct "active" teacher effects but also through implicit behaviors that enhance students' willingness to pursue post-secondary studies in the same fields.

These two channels also form the basis of the heterogeneous effects analysis, which shows that teachers with higher cognitive abilities are found to lead to higher gains especially among students with stronger aptitude and same-gender student-teacher matches.

Given the great importance of STEM knowledge for technological innovation and economic productivity growth, this study reveals the strong positive externalities of high-quality science teachers. The long-term effects we found emphasize the contribution of teacher quality to the economy as a whole, not just to the students themselves. By promoting STEM higher education and higher quality post-secondary institutions, teacher quality helps increase the supply of qualified graduates in high-demand professions and productivity-enhancing sectors of the Israeli economy, such as the high-tech industry. For continued research, it would be interesting to examine whether teachers' cognitive abilities are associated with even longer-term outcomes for students, such as productivity at work, income, and industry of employment.

An important limitation of our study is the sample of teachers who uniquely teach their subject at school. This constraint has resulted in a sample that is not representative of the entire education system in Israel, which may limit the generalizability of our findings. Our final sample consists mostly of smaller schools located in peripheral areas with students from lower socioeconomic backgrounds. However, these schools largely correspond to the profile of schools that are the focus of education policy.[49]

Given the great importance of STEM knowledge for technological innovation and economic productivity growth, this study has several policy implications. First, it supports policies and reforms aimed at recruiting and compensating cognitively skilled teachers in STEM subjects. Second, it suggests that reforms aimed at increasing the number of students pursuing STEM fields in high school might be more effective when attention is paid to teacher quality as well. Finally, from a policy perspective, our findings highlight significant educational gains from exposure to teachers with strong cognitive skills, particularly for students with stronger aptitude. In terms of efficiency, this suggests that investing in teacher quality in stronger areas and among stronger students yields greater returns. However, given that achievement gaps between socioeconomic groups in Israel remain relatively large, addressing inequality would require prioritizing investments in teacher quality for weaker areas and students, to better support those with lower aptitude and those attending underperforming schools. It is important to note that this study focused on high school teachers and students in advanced science subjects. Consequently, the external validity of these findings to more foundational studies, particularly at earlier educational stages, is limited. This limitation is evident, for example, in previous research that has shown teacher quality to be a crucial factor in improving educational outcomes and basic skills at earlier stages of schooling, especially for students from low socioeconomic backgrounds—heterogeneous effects that are not observed in this study.

[49] See, for example, recommendations from the Bank of Israel Special Report: "Four Recommended Pillars of Strategic Government Action to Accelerate Economic Growth and A Fiscal Framework for Financing Them", Bank of Israel 2021.

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ONLINE APPENDIX

Table A1: Summary Statistics of Sample Schools Compared to Science Matriculating Schools, 2012–2019

	Jewish Schools		Arab Schools	
	Final Sample Schools	Science Matriculating Schools	Final Sample Schools	Science Matriculating Schools
Panel A: Advanced Science Students' Characteristics				
Number of Siblings	2.59	2.35	4.65	4.06
Proportion of Female Students	0.55	0.50	0.64	0.63
Ethnicity[2]				
Proportion of Asia-Africa	0.53	0.47	0.04	0.03
Proportion of America-Europe	0.25	0.30	0.00	0.01
Proportion of Former Soviet Union	0.19	0.19	0.00	0.00
Proportion of Israel	0.03	0.04	0.96	0.96
Father's Years of Schooling	14.02	14.44	11.23	11.68
Mother's Years of Schooling	14.35	14.69	10.82	11.49
Previous GEMS Test Score[3]	0.53	0.64	0.14	0.22
Science Matriculation Score (Raw)[4]	82.66	84.50	77.61	78.81
Science Matriculation Score (Standardized)[4]	0.03	0.18	-0.34	-0.24
Proportion Acquiring Post-Secondary Education[5]	0.29	0.33	0.39	0.41
Proportion Acquiring Post-Secondary Education in Research University[5]	0.14	0.17	0.13	0.16
Proportion of Acquiring STEM Post-Secondary Education Major Subject[5]	0.13	0.17	0.09	0.11
Total Number of Students	16,440	149,376	27,097	88,340
Number of Students Per School / Year	35.43	49.19	52.72	67.54
Panel B: Schools' Characteristics				
Socioeconomic Cluster of School Locality	5.09	5.68	2.69	2.89
Proportion of Jewish-Religious Schools	0.53	0.40	0.00	0.00
Proportion of Peripheral Schools[6]	0.45	0.33	0.68	0.67
Total Number of Schools / Year	464	3,037	514	1,308
Panel C: Science Teachers' Characteristics[7]				
Age	43.51	49.69	37.60	41.20
Proportion of Immigrants	0.25	0.30	0.01	0.03
Proportion of Female Teachers	0.66	0.68	0.50	0.46
Number of Children	3.26	3.05	2.81	3.00
Total Number of Teachers / Year	1,371	12,591	1,876	5,787

Notes: This table compares the summary statistics of the sample schools with those of all advanced science matriculating schools. Thus, the students' characteristics refer to all advanced-level science matriculation students in school, not only those of the final sample, and the teachers' characteristics similarly refer to all science matriculation teachers in school.

1. The advanced science students in the final school sample are compared to advanced science students in high schools that offer at least one advance science matriculation course.
2. Students born, or with parents or grandparents born, in Asia/Africa, Europe/America, the Former Soviet Union, or in Israel.
3. The GEMS records (Growth and Effectiveness Measures for Schools) include test scores of fifth and eighth graders of half of the schools in Israel each year, so that each school participates in GEMS tests once every two years. We standardized these GEMS test scores in each of four subjects (Hebrew, English, mathematics, and science), year, and grade, and average them for each student. The final standardized GEMS score considered for each student is the average 8th grade score (or earlier 5th grade score for those with no 8th grade test score).
4. Raw scores are ranged from 0 to 100. The standardization is based on the graduation cycle and the subject, including all examined students.
5. Starting post-secondary education until up to six years after the end of high school.
6. The periphery indicator equals one if the geographic district is far from the population centers defined as the Central District, Tel Aviv District, Haifa District, and Jerusalem District.
7. The science matriculation teachers in the school sample are compared to science matriculation teachers in high schools that offer at least one advance science matriculation course.

Table A2

Summary Statistics of Sample Teachers' Cognitive Ability Measures

	Mean	SD	Median	Min	Max
Proportion with Advanced Academic Degree	0.32	0.47		0.00	1.00
Math Matriculation Test Score (Standardized)[1]	1.14	0.76	0.95	-1.56	2.34
Psychometric Math Score (Standardized)[2]	0.68	0.91	0.75	-1.70	2.52

Notes

1. In order to take into account the difficulty gap between different levels of study, math matriculation test scores are weighted and bonuses are added based on the number of credit units taken, as computed by the Ministry of Education and the universities. These grades are then transformed into z-scores by each year and each subject.
2. Psychometric math scores are standardized by test year.

Table A3

Binary Measures of Teachers' Cognitive Ability Effects on Students' Science Matriculation Test Scores

	Science Matriculation Test Scores (1)	Post-Secondary Education (2)	Quality of Post-Secondary Education (3)	Orientation of Post-Secondary Education (4)
Advanced Academic Degree	0.038	-0.024	0.008	0.033*
	(0.045)	(0.028)	(0.027)	(0.018)
Math Matriculation Test Score	0.068	0.017	0.056**	0.038*
I(x) = [x > med{X}]	(0.044)	(0.029)	(0.026)	(0.021)
Psychometric Math Score	0.009	-0.005	0.009	0.009
I(x) = [x > med{X}]	(0.050)	(0.027)	(0.030)	(0.024)
School Year FE	V	V	V	V
Matriculation Subject FE	V	V	V	V
School Locality FE	V	V	V	V
Teachers' Cha.	V	V	V	V
Students' Cha.	V	V	V	V

Notes*:* These regressions examine the effects of teachers' cognitive abilities on students' academic outcomes. The short-term dependent variable is as in Table 3: the students' matriculation test scores (Column 1). The long-term dependent variables are as in Table 4: the probability of our sample students pursuing post-secondary education up to six years after the end of high school (Column 2); the probability of pursuing post-secondary education at a research university (Column 3); and the probability of pursuing post-secondary education in STEM major subjects (Column 4). The explanatory variables are our three measures of teachers' cognitive abilities as in Table 5 (where the variables for the teacher’s math matriculation test and psychometric math scores are dummies that equal 1 if the teacher's score equals the median score value or higher among the sample teachers, and 0 otherwise (Rows 2 and 3)). In all columns the explanatory variables enter the analysis separately and include controls for the fixed effects of the school's locality, the school year, and the matriculation subject, as well as teachers' and students' characteristics. The teachers' and students' characteristics included are the same as in Table 3. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A4

Effects of Teachers' Cognitive Ability on Students' Science Raw Matriculation Test Score

	Separate				Joint			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Advanced Academic Degree	2.544***	1.165**	0.590	0.503	1.804**	0.862	0.347	0.295
	(0.73)	(0.56)	(0.58)	(0.54)	(0.762)	(0.56)	(0.58)	(0.54)
Math Matriculation Test Score	1.551***	0.459	0.847**	0.846**	-0.19	0.443	0.748*	0.794**
	(0.46)	(0.39)	(0.38)	(0.34)	(0.515)	(0.41)	(0.42)	(0.39)
Psychometric Math Score	2.51***	0.118	0.263	0.260	2.397***	-0.138	-0.109	-0.118
	(0.38)	(0.36)	(0.38)	(0.35)	(0.464)	(0.39)	(0.42)	(0.40)
School Year FE		V	V	V		V	V	V
Matriculation Subject FE		V	V	V		V	V	V
School Locality FE		V	V	V		V	V	V
Teachers' Cha.			V	V			V	V
Students' Cha.				V				V
Observations					17,616	17,616	17,616	16,587

Notes*:* These regressions are equivalent to those presented in Table 3, but instead of standardized students' matriculation test scores, the dependent variable now is the raw matriculation score (ranged between 0 and 100) in Biology, Physics, Chemistry, and Computer Science. The explanatory variables remain as in Table 3. In Columns 1–4 the explanatory variables are included separately in the regression, while in Columns 5–8 they are included jointly in the same regression. Columns 1 and 5 are simple OLS regressions. Columns 2 and 6 add controls for the fixed effects of the school's locality, the school year, and the matriculation subject. Columns 3 and 7 add teachers' characteristics, and Columns 4 and 8 also add students' characteristics. Teachers' and students' characteristics are the same as in Table 3. The number of observations varies slightly across the separated regressions in Columns 1–4 but is not lower than the number of observations in the corresponding joint regression from Columns 5–8. Standard errors are reported in parentheses and are clustered by teacher's ID. *** p<0.01, ** p<0.05, * p<0.1

Table A5

Probit Estimation of Teachers' Cognitive Ability Long-Term Effects on Students' Academic Outcomes

	Post-Secondary Education		Quality of Post-Secondary Education		Orientation of Post-Secondary Education	
	Separate	**Joint**	**Separate**	**Joint**	**Separate**	**Joint**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
High Academic Degree	-0.020	-0.012	-0.008	-0.009	0.024	0.03*
	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
Math Matriculation Test Score	0.017	0.003	0.047***	0.05***	0.047***	0.043***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Psychometric Math Score	0.026*	0.025	0.024	-0.001	0.024**	0.003
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
School Year FE	V	V	V	V	V	V
Matriculation Subject FE	V	V	V	V	V	V
School Locality FE	V	V	V	V	V	V
Teachers' Cha.	V	V	V	V	V	V
Students' Cha.	V	V	V	V	V	V
Observations		5,470		5,391		5,176

Notes*:* This table presents the main results of an alternative estimation by probit regressions of the long-term effects of teachers' cognitive abilities on students' academic outcomes. The reported numbers are the estimated marginal effects. The dependent and explanatory variables are the same as in Table 4. In the odd-numbered columns the explanatory variables are included separately in the regression, while in the even-numbered columns they are included jointly in the same regression. All columns include controls for the fixed effects of the school's locality, the school year, and the matriculation subject, as well as teachers' and students' characteristics. Teachers' and students' characteristics included are the same as in Table 3. The number of observations varies slightly across the separate regressions but is not lower than the number of observations in the corresponding joint regression. Standard errors are reported in parentheses and are clustered by teacher's ID. *** p<0.01, ** p<0.05, * p<0.1

Table A6

Effects of Teachers' Cognitive Ability on Students' Educational Outcomes, Including All Credit Unit Levels

	Science Matriculation Test Scores		Post-Secondary Education		Quality of Post-Secondary Education		Orientation of Post-Secondary Education	
	Separate	**Joint**	**Separate**	**Joint**	**Separate**	**Joint**	**Separate**	**Joint**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Advanced Academic Degree	0.086*	0.038	-0.059**	-0.054*	0.002	0.012	0.019	0.024
	(0.046)	(0.045)	(0.029)	(0.028)	(0.025)	(0.025)	(0.019)	(0.017)
Math Matriculation Test Score	0.094***	0.069**	0.048***	0.034*	0.045***	0.029*	0.053***	0.039***
	(0.028)	(0.033)	(0.015)	(0.018)	(0.014)	(0.016)	(0.013)	(0.013)
Psychometric Math Score	0.059**	0.023	0.051***	0.030*	0.041***	0.025**	0.045***	0.023*
	(0.028)	(0.033)	(0.014)	(0.016)	(0.011)	(0.012)	(0.012)	(0.012)
School Year FE	V	V	V	V	V	V	V	V
Matriculation Subject FE	V	V	V	V	V	V	V	V
School Locality FE	V	V	V	V	V	V	V	V
Teachers' Cha.	V	V	V	V	V	V	V	V
Students' Cha.	V	V	V	V	V	V	V	V
Observations		**20,839**		**8,235**		**8,235**		**8,167**

Notes*:* These regressions examine the effects of teachers' cognitive abilities on students' academic outcomes, including any level of credit units (1–10 credit unit levels compared with minimum 5 credit units in our final sample). The short-term dependent variable is as in Table 3: the students' matriculation test scores (Columns 1–2). The long-term dependent variables are as in Table 4: the probability of our sample students pursuing post-secondary education up to six years after the end of high school (Columns 3–4); the probability of pursuing post-secondary education at a research university (Columns 5–6); and the probability of pursuing post-secondary education in STEM major subjects (Columns 7–8). The explanatory variables are our three measures of teachers' cognitive abilities as in Tables 3 and 4. In the odd-numbered columns the explanatory variables are included separately in the regression, while in the even-numbered columns they are included jointly in the same regression. All columns include controls for the fixed effects of the school's locality, the school year, and the matriculation subject, as well as teachers' and students' characteristics. The teachers' and students' characteristics included are the same as in Table 3. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A7

Effects of Teachers' Cognitive Ability on Students' Educational Outcomes, Controlling for Students' Previous Test Scores

	Science Matriculation Test Scores		Post-Secondary Education		Quality of Post-Secondary Education		Orientation of Post-Secondary Education	
	Separate	**Joint**	**Separate**	**Joint**	**Separate**	**Joint**	**Separate**	**Joint**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Advanced Academic Degree	-0.009	-0.013	-0.041	-0.033	-0.008	-0.008	0.020	0.027
	(0.046)	(0.047)	(0.026)	(0.028)	(0.025)	(0.026)	(0.018)	(0.018)
Math Matriculation Test Score	0.054*	0.058*	0.022	0.009	0.044**	0.04**	0.043***	0.029*
	(0.028)	(0.032)	(0.018)	(0.021)	(0.019)	(0.019)	(0.013)	(0.015)
Psychometric Math Score	-0.006	-0.035	0.024	0.020	0.028	0.010	0.026**	0.014
	(0.032)	(0.037)	(0.016)	(0.020)	(0.017)	(0.018)	(0.012)	(0.013)
School Year FE	V	V	V	V	V	V	V	V
Matriculation Subject FE	V	V	V	V	V	V	V	V
School Locality FE	V	V	V	V	V	V	V	V
Teachers' Cha.	V	V	V	V	V	V	V	V
Students' Cha.	V	V	V	V	V	V	V	V
Students' GEMS Score	V	V	V	V	V	V	V	V
Observations		13,621		4,871		4,871		4,826

Notes*:* The short-term dependent variable is as in Table 3—the students' matriculation test scores (Columns 1–2). The long-term dependent variables are as in Table 4: the probability of our sample students pursuing post-secondary education up to six years after the end of high school (Columns 3–4); the probability of pursuing post-secondary education at a research university (Columns 5–6); and the probability of pursuing post-secondary education in STEM major subjects (Columns 7–8). The explanatory variables are our three measures of teachers' cognitive abilities as in Tables 3 and 4. In all columns the explanatory variables enter the analysis separately and include controls for the fixed effects of the school's locality, the school year, and the matriculation subject, as well as teachers' and students' characteristics, and students' GEMS scores. The teachers' and students' characteristics included are the same as in Table 3. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A8

Short- and Long-Term Effects of Teachers' Cognitive Ability on Students' Educational Outcomes from a PSM Analysis, Controlling for Students' Previous Test Scores

	Science Matriculation Test Score		Post-Secondary Education		Quality of Post-Secondary Education		Orientation of Post-Secondary Education	
	KBM	**NNM**	**KBM**	**NNM**	**KBM**	**NNM**	**KBM**	**NNM**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Advanced Academic Degree	0.030	0.030	-0.017	-0.019	-0.024	-0.020	-0.001	-0.006
	(0.021)	(0.025)	(0.020)	(0.026)	(0.017)	(0.025)	(0.016)	(0.024)
Math Matriculation Test Score	0.037	0.038	0.006	0.020	0.101***	0.078***	0.036*	0.053**
I(x) = [x > med{X}]	(0.023)	(0.026)	(0.033)	(0.027)	(0.024)	(0.024)	(0.022)	(0.026)
Psychometric Math Score	0.053*	0.022	0.020	-0.005	0.064**	0.016	0.078***	0.042
I(x) = [x > med{X}]	(0.031)	(0.034)	(0.037)	(0.032)	(0.027)	(0.030)	(0.023)	(0.030)
School Year FE	V	V	V	V	V	V	V	V
Matriculation Subject FE	V	V	V	V	V	V	V	V
Locality District FE	V	V	V	V	V	V	V	V
Locality Socioeconomic Cluster FE	V	V	V	V	V	V	V	V
Teacher's Cha.	V	V	V	V	V	V	V	V
Student's Cha.	V	V	V	V	V	V	V	V
Students' GEMS Score	V	V	V	V	V	V	V	V
Common Support Imposed	Yes		Yes		Yes		Yes	

Notes*:* This table presents PSM results equivalently to Table 5, adding controls for students' previous GEMS scores. We employ two matching methods—kernel-based matching (KBM), and nearest-neighbors matching (NNM) with 3 nearest neighbors. Due to cost-effectiveness considerations, we bootstrap the analysis (500 replications) only for the NNM specifications, and report the bootstrapped standard errors for those specifications only (even-numbered columns). The short-term dependent variable is as in Table 3—the students' matriculation test scores (Columns 1–2). The long-term dependent variables are as in Table 4: the probability of our sample students pursuing post-secondary education up to six years after the end of high school (Columns 3–4); the probability of pursuing post-secondary education at a research university (Columns 5–6); and the probability of pursuing post-secondary education in STEM major subjects (Columns 7–8). The explanatory variables are the same as in Table 5. In all columns the explanatory variables enter the analysis separately and include controls for the fixed effects of the school locality's district, the school locality's socioeconomic cluster, the school year, and the matriculation subject, as well as teachers' and students' characteristics, and students' GEMS scores. The teachers' and students' characteristics included are the same as in Table 3. Finally, in all specifications the common support is imposed. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A9

Effects of Teachers' Cognitive Ability on Students' Educational Outcomes, Controlling for the School Quality of Teachers

	Science Matriculation Test Scores		Post-Secondary Education		Quality of Post-Secondary Education		Orientation of Post-Secondary Education	
	Separate	Joint	Separate	Joint	Separate	Joint	Separate	Joint
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Advanced Academic Degree	0.021	0.009	-0.021	-0.006	-0.005	-0.009	0.029	0.033*
	(0.045)	(0.046)	(0.029)	(0.032)	(0.027)	(0.027)	(0.018)	(0.018)
Math Matriculation Test Score	0.079***	0.079**	0.013	0.001	0.058***	0.056***	0.046***	0.033*
	(0.028)	(0.033)	(0.018)	(0.021)	(0.021)	(0.021)	(0.015)	(0.018)
Psychometric Math Score	0.020	-0.018	0.024	0.024	0.037**	0.011	0.029**	0.013
	(0.029)	(0.033)	(0.015)	(0.019)	(0.018)	(0.018)	(0.013)	(0.014)
School Year FE	V	V	V	V	V	V	V	V
Matriculation Subject FE	V	V	V	V	V	V	V	V
School Locality FE	V	V	V	V	V	V	V	V
Teachers' Cha.	V	V	V	V	V	V	V	V
Students' Cha.	V	V	V	V	V	V	V	V
School's Academic Level of Teachers	V	V	V	V	V	V	V	V
Observations		16,587		5,492		5,492		5,439

Notes*:* These regressions examine the effects of teachers' cognitive abilities on students' academic outcomes, adding controls for the proportion of all teachers in the school with advanced academic degrees. The short-term dependent variable is as in Table 3—the students' matriculation test scores (Columns 1–2). The long-term dependent variables are as in Table 4: the probability of our sample students pursuing post-secondary education up to six years after the end of high school (Columns 3–4); the probability of pursuing post-secondary education at a research university (Columns 5–6); and the probability of pursuing post-secondary education in STEM major subjects (Columns 7–8). The explanatory variables are our three measures of teachers' cognitive abilities as in Tables 3 and 4. In all columns the explanatory variables enter the analysis separately and include controls for the fixed effects of the school's locality, the school year, and the matriculation subject, as well as teachers' and students' characteristics, and students' GEMS scores. The teachers' and students' characteristics included are the same as in Table 3. Standard errors are reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A10

Effects of Teachers' Cognitive Ability on Students' Educational Outcomes, Controlling for School Parental Earning

	Science Matriculation Test Scores		Post-Secondary Education		Quality of Post-Secondary Education		Orientation of Post-Secondary Education	
	Separate	Joint	Separate	Joint	Separate	Joint	Separate	Joint
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Advanced Academic Degree	0.035	0.022	-0.019	-0.010	0.014	0.014	0.037**	0.043**
	(0.042)	(0.044)	(0.028)	(0.030)	(0.027)	(0.028)	(0.018)	(0.019)
Math Matriculation Test Score	0.055**	0.063**	0.018	0.007	0.051**	0.052**	0.042***	0.032*
	(0.027)	(0.031)	(0.018)	(0.022)	(0.021)	(0.022)	(0.015)	(0.017)
Psychometric Math Score	0.005	-0.025	0.023	0.020	0.028	0.003	0.024*	0.009
	(0.028)	(0.032)	(0.015)	(0.019)	(0.018)	(0.018)	(0.013)	(0.014)
School Year FE	V	V	V	V	V	V	V	V
Matriculation Subject FE	V	V	V	V	V	V	V	V
School Locality FE	V	V	V	V	V	V	V	V
Teachers' Cha.	V	V	V	V	V	V	V	V
Students' Cha.	V	V	V	V	V	V	V	V
School's Parental Earning	V	V	V	V	V	V	V	V
Observations		16,587		5,492		5,492		5,439

Notes*:* These regressions examine the effects of teachers' cognitive abilities on students' academic outcomes, adding controls for the mean level of parents' income in the school, based on all 12th grade students in the school. A student's parents' income is calculated as the average of both parents' total annual income during the student's high school ages (15–17). The short-term dependent variable is as in Table 3—the students' matriculation test scores (Columns 1–2). The long-term dependent variables are as in Table 4: the probability of our sample students pursuing post-secondary education up to six years after the end of high school (Columns 3–4); the probability of pursuing post-secondary education at a research university (Columns 5–6); and the probability of pursuing post-secondary education in STEM major subjects (Columns 7–8). The explanatory variables are our three measures of teachers' cognitive abilities as in Tables 3 and 4. In all columns the explanatory variables enter the analysis separately and include controls for the fixed effects of the school's locality, the school year, and the matriculation subject, as well as teachers' and students' characteristics, and students' GEMS scores. The teachers' and students' characteristics included are the same as in Table 3. Standard errors are reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A11

Effects of Teachers' Cognitive Ability on the Probability of Pursuing Advanced Level Science Matriculation Exams

	Separate				Joint			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Advanced Academic Degree	0.011	-0.012	-0.012	-0.007	0.021**	-0.009	-0.009	-0.005
	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)	(0.011)	(0.010)
Math Matriculation Test Score	-0.01	0.003	0.004	0.002	0.004	0.002	0.000	-0.001
	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)
Psychometric Math Score	-0.02***	0.005	0.009	0.006	-0.024***	0.003	0.007	0.005
	(0.007)	(0.006)	(0.006)	(0.006)	(0.008)	(0.007)	(0.008)	(0.008)
School Year FE		V	V	V		V	V	V
Matriculation Subject FE		V	V	V		V	V	V
School Locality FE		V	V	V		V	V	V
Teachers' Cha.			V	V			V	V
Students' Cha.				V				V
Observations					122,903	122,903	122,903	116,159

Notes*:* These regressions examine the effects of teachers' cognitive abilities on students' probability of pursuing advanced level matriculation exams (minimum 5 credit units) in science subjects (Biology, Physics, Chemistry, and Computer Science). In other words, they examine the effects of teachers' cognitive abilities on the inclusion of a student in our final sample. The explanatory variables are the same as in Tables 3 and 4. In Columns 1–4 the explanatory variables are included seperately in the regression, while in Columns 5–8 they are included jointly in the same regression. Columns 1 and 5 are simple OLS regressions. Columns 2 and 6 add controls for the fixed effects of the school's locality, the school year, and the matriculation subject. Columns 3 and 7 add teachers' characteristics, and Columns 4 and 8 add also students' characteristics. Teachers' and students' characteristics included are the same as in Table 3. The number of observations varies slightly across the separated regressions in Columns 1–4 but is not lower than the number of observations in the corresponding joint regression from Columns 5–8. Standard errors are reported in parentheses and are clustered by teacher’s ID. *** p<0.01, ** p<0.05, * p<0.1

Table A12

Effects of Teachers' Cognitive Ability on the Probability of Pursuing Any Level of Science Matriculation Exams

	Separate				Joint			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Advanced Academic Degree	0.003	-0.007	-0.006	-0.002	0.019	-0.001	0.001	0.005
	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
Math Matriculation Test Score	-0.03***	-0.006	-0.005	-0.006	-0.004	0.004	0.001	0.000
	(0.009)	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)	(0.010)
Psychometric Math Score	-0.04***	-0.013	-0.009	-0.012	-0.041***	-0.016*	-0.012	-0.014
	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)	(0.010)
School Year FE		V	V	V		V	V	V
Matriculation Subject FE		V	V	V		V	V	V
School Locality FE		V	V	V		V	V	V
Teachers' Cha.			V	V			V	V
Students' Cha.				V				V
Observations					122,903	122,903	122,903	116,159

Notes: These regressions examine the effects of teachers' cognitive abilities on students' probability of pursuing any level of matriculation exam (110 credit units) in science subjects (Biology, Physics, Chemistry, and Computer Science). The explanatory variables are the same as in Tables 3 and 4. In Columns 1–4 the explanatory variables are included separately in the regression, while in Columns 5–8 they are included jointly in the same regression. Columns 1 and 5 are simple OLS regressions. Columns 2 and 6 add controls for the fixed effects of the school's locality, the school year, and the matriculation subject. Columns 3 and 7 add teachers' characteristics, and Columns 4 and 8 add also students' characteristics. Teachers' and students' characteristics included are the same as in Table 3. The number of observations varies slightly across the separated regressions in Columns 1–4 but is not lower than the number of observations in the corresponding joint regression from Columns 5–8. Standard errors are reported in parentheses and are clustered by teacher's ID. *** p<0.01, ** p<0.05, * p<0.1

Table A13

Effects of Teachers' Cognitive Ability on Students' Educational Outcomes, Controlling for Class Size

	Science Matriculation Test Scores		Post-Secondary Education		Quality of Post-Secondary Education		Orientation of Post-Secondary Education	
	Separate	Joint	Separate	Joint	Separate	Joint	Separate	Joint
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Advanced Academic Degree	0.039	0.020	-0.013	-0.001	0.009	0.012	0.040*	0.047**
	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Math Matriculation Test Score	0.078***	0.081**	0.020	0.006	0.051**	0.048**	0.042***	0.031*
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Psychometric Math Score	0.018	-0.021	0.025	0.023	0.031*	0.008	0.026*	0.011
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
School Year FE	V	V	V	V	V	V	V	V
Matriculation Subject FE	V	V	V	V	V	V	V	V
School Locality FE	V	V	V	V	V	V	V	V
Teachers' Cha.	V	V	V	V	V	V	V	V
Students' Cha.	V	V	V	V	V	V	V	V
Class Size	V	V	V	V	V	V	V	V
Observations		16,587		5,492		5,492		5,439

Notes: The short-term dependent variable is as in Table 3—the students' matriculation test scores (Columns 1–2). The long-term dependent variables are as in Table 4: the probability of our sample students pursuing post-secondary education up to six years after the end of high school (Columns 3–4); the probability of pursuing post-secondary education at a research university (Columns 5–6); and the probability of pursuing post-secondary education in STEM major subjects (Columns 7–8). The explanatory variables are our three measures of teachers' cognitive abilities as in Tables 3 and 4. In all columns the explanatory variables enter the analysis separately and include controls for the fixed effects of the school's locality, the school year, and the matriculation subject, as well as teachers' and students' characteristics, and students' GEMS scores. The teachers' and students' characteristics included are the same as in Table 3. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A14

Effects of Teachers' Cognitive Ability on Students' Educational Outcomes, Controlling for Teacher's Full Time Equivalent

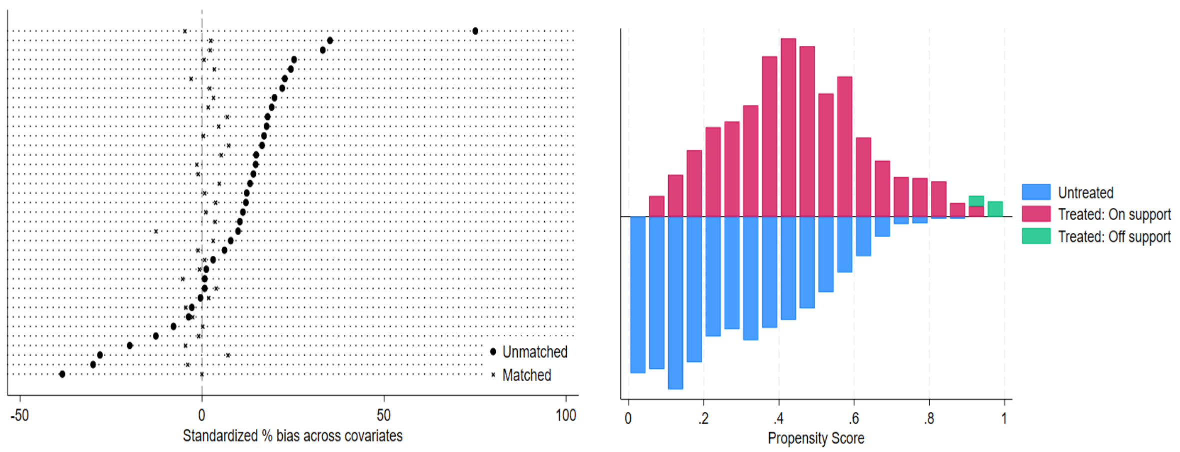
	Science Matriculation Test Scores		Post-Secondary Education		Quality of Post-Secondary Education		Orientation of Post-Secondary Education	
	Separate	Joint	Separate	Joint	Separate	Joint	Separate	Joint
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Advanced Academic Degree	0.038	0.019	-0.027	-0.014	0.008	0.010	0.030*	0.039**
	(0.045)	(0.045)	(0.028)	(0.030)	(0.027)	(0.028)	(0.018)	(0.019)
Math Matriculation Test Score	0.077***	0.079**	0.017	0.005	0.051**	0.048**	0.041***	0.031*
	(0.028)	(0.033)	(0.017)	(0.021)	(0.021)	(0.022)	(0.014)	(0.016)
Psychometric Math Score	0.017	-0.021	0.024	0.023	0.030*	0.008	0.024*	0.010
	(0.029)	(0.033)	(0.015)	(0.018)	(0.018)	(0.018)	(0.013)	(0.014)
School Year FE	V	V	V	V	V	V	V	V
Matriculation Subject FE	V	V	V	V	V	V	V	V
School Locality FE	V	V	V	V	V	V	V	V
Teachers' Cha.	V	V	V	V	V	V	V	V
Students' Cha.	V	V	V	V	V	V	V	V
Teachers' FTE	V	V	V	V	V	V	V	V
Observations		16,587		5,492		5,492		5,439

Notes: The short-term dependent variable is as in Table 3—the students' matriculation test scores (Columns 1–2). The long-term dependent variables are as in Table 4: the probability of our sample students pursuing post-secondary education up to six years after the end of high school (Columns 3–4); the probability of pursuing post-secondary education at a research university (Column 5–6); and the probability of pursuing post-secondary education in STEM major subjects (Columns 7–8). The explanatory variables are our three measures of teachers' cognitive abilities as in Tables 3 and 4. In all columns the explanatory variables enter the analysis separately and all include controls for the fixed effects of the school's locality, the school year, and the matriculation subject, as well as teachers' and students' characteristics, and students' GEMS scores. The teachers' and students' characteristics included are the same as in Table 3. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

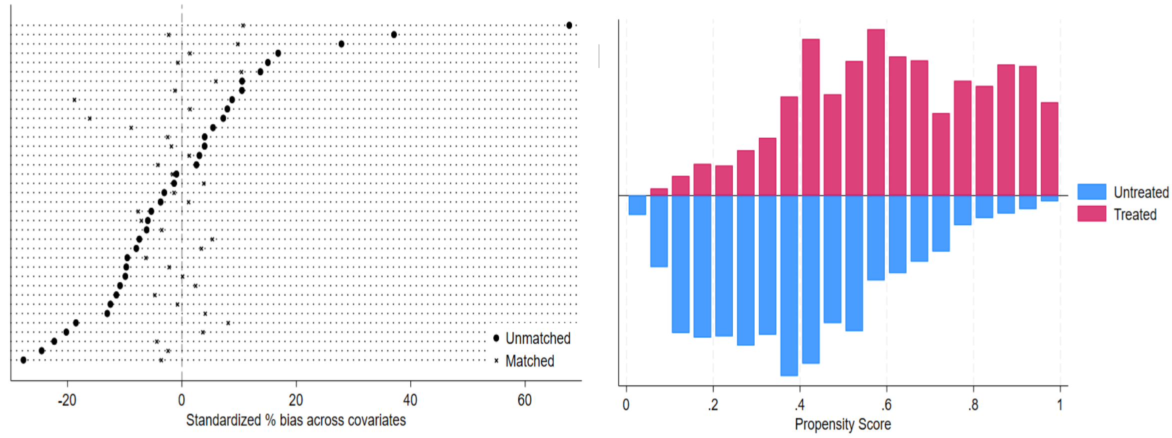
Appendix Figure A1:
Quality Assesment of PSM Analysis for the Short-Term Effects of Teachers' Cognitive Ability

Balancing Property	**Common Support Property**

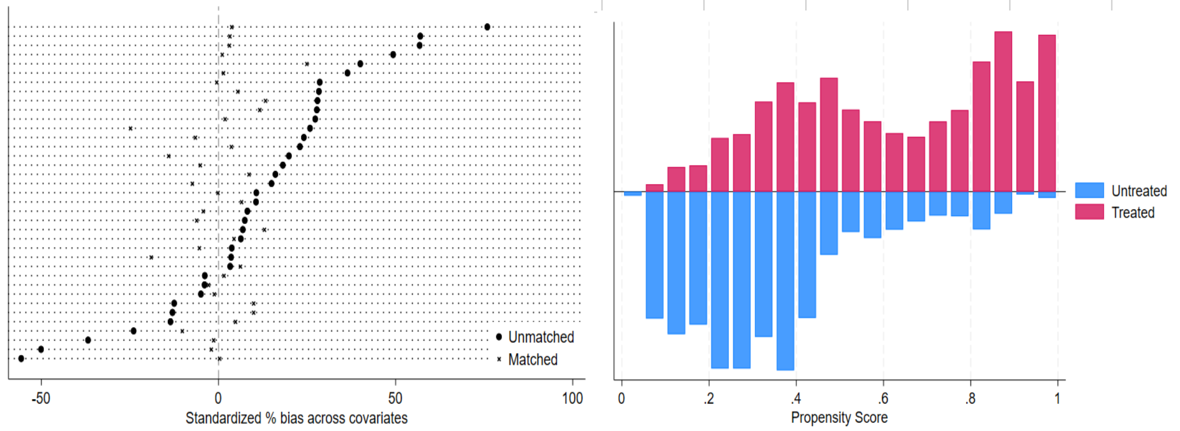
Panel A. Advanced Academic Degree



Panel B. Math Matriculation Test Score (Binary)



Panel C. Psychometric Math Test Score (Binary)



Notes: This table presents tests assessing the quality of the main propensity score matching analysis employed in this research. The graphs above refer only to the results presented in Column 1 of Table 5 (students' matriculation scores as the outcome variable). Panel A refers to PSM results when the treatment variable is holding an advanced academic degree (M.A. or Ph.D.), Panel B refers to when the treatment variable is teachers' having a high math matriculation score; and Panel C refers to when the treatment variable is teachers' having high Psychometric math score. The left graphs assess the balancing property (by using the *pstest* command in Stata), showing the standardized percentage bias across the covariates that are included in the analysis, among both the unmatched and matched samples (each dotted line represents a covariate). The Rubin's B (R) measurement is reduced from 100.0 (0.68) in the unmatched sample to 21.9 (0.89) in the matched sample when the treatment variable is an advanced academic degree, from 108.5 (1.27) to 37.4 (1.07) when the treatment variable is high math matriculation score, and from 123.0 (2.1) to 49.3 (1.0) when the treatment variable is high Psychometric math score. The right graphs assess the common support property (by using the *psgraph* command in Stata), showing the distribution of the propensity score among both the treatment and control groups. The existence of the common support property is imposed on the analysis by using the *common* command in Stata, which drops treatment observations for which the p-score is higher than the maximum or lower than the minimum p-score of the controls (as you can see, for example, in the green bar parts of the common support graph in Panel A).