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Abstract

We examine the impact of students' classroom rank in math on educational, occupational, and labor-market outcomes. Using Swiss PISA-2012 data linked to administrative student records and tax information, and leveraging variations in achievement distribution across classes, we find that students with higher math ranks are more likely to pursue STEM-related occupations. Through subject-specific survey questions, we provide evidence of the underlying mechanisms at play, and we also demonstrate that parents can serve as important mediators. Furthermore, we show that a higher classroom rank in math increases earnings and the willingness to invest in occupation-specific further education.

Keywords: Ordinal rank, Peer effects, Occupational choices, Earnings, Human capital investments
JEL Classification: I21, I24, J24, J31

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1 Introduction

Occupational choices play an important role in both individual labor market outcomes, including income and career trajectories (Grogger and Eide, 1995; Altonji et al., 2012, 2014), and the overall skill composition of the workforce, contributing to broader economic dynamics (Patnaik et al., 2020). Previous studies have uncovered several factors that influence occupational choices, including beliefs about occupation-related characteristics, individual attributes such as ability, and the school environment such as teachers and classroom composition (e.g., Arcidiacono, 2004; Wiswall and Zafar, 2015; Brenøe and Zölitz, 2020).[1] An important aspect of classroom composition, which has received so far limited attention in the context of occupational choices, is students' ordinal rank in the classroom.

While canonical models of occupational choice assume that individuals possess perfect information about both job attributes and their own skills (Roy, 1951; Rosen, 1974), students often face significant uncertainty when making educational and occupational decisions (Stinebrickner and Stinebrickner, 2014). Lacking perfect information on their own (true) abilities, and hence, on the set of skills they can employ on specific occupations, students may compare themselves to their peers to assess their abilities (Murphy and Weinhardt, 2020). Therefore, a student's subject-specific rank—defined as their ordinal position within their peer group's subject-specific ability distribution—can be an important factor, in addition to actual ability, influencing their educational and occupational choices.

In this paper, we explore how a student's rank in specific subjects during compulsory schooling impacts their occupational choices, earnings, and investments in further education. Previous research has shown that academic self-concepts may be subject-specific (Marsh et al., 1988). Building on earlier research, that has demonstrated the importance of math skills for individual and societal outcomes compared to other skills (Arcidiacono, 2004; Weinberger, 2014; Hanushek et al., 2015), and policymakers' interest in understanding STEM-related decisions, our primary focus centers on a student's ranking in the math ability distribution and its association with the likelihood of pursuing careers in STEM fields.

We study this question in the context of the Swiss vocational education and training system using a unique data set that combines the Swiss PISA-2012 student assessment test with

[1] For a review of the literature see e.g. Altonji et al. (2016) and Patnaik et al. (2020).

longitudinal administrative education records, new data on occupations skill requirements, and income information from tax records. Our extensive set of data enables us to establish connections between students' classroom rank in lower-secondary schools in various subjects (assessed through PISA-2012 test scores) and their subsequent occupational choices, their outcomes in the labor market, and their educational investments up to 8 years later.

In our empirical analysis, we build upon recent studies and leverage quasi-random variation in the math ability distributions across classrooms (Murphy and Weinhardt, 2020; Denning et al., 2023). We employ regression models that account for classroom-specific factors and include comprehensive controls for students' math abilities. This allows us to examine how a student's math rank in the classroom influences their occupational choices and other labor market outcomes. Using specific questions about attitudes towards math in the PISA-2012 background questionnaires, we investigate the underlying mechanisms. Finally, we investigate whether decisions based on perceived rather than actual ability result in higher dropout rates and changes of the initial training occupations.

We document results for three sets of outcome variables - occupational choices, income, and investments in additional human capital. First, our findings reveal that being ranked at the top of the distribution in the classroom, as opposed to the bottom, significantly increases the probability of selecting a training occupation with high STEM requirements after compulsory schooling. More specifically, we find an approximately 9 percentage points increase in the probability of choosing a training occupation that is positioned in the 4th decile of the STEM skill requirement distribution, or a 40% increase relative to the sample mean.

To shed light on the mechanisms behind this effect, we show that classroom rank in math is positively associated with interest in math, perceived math ability, and willingness to study math. This is in line with theoretical models outlined in Azmat and Iriberri (2010) and Kiessling and Norris (2023) in which students are uncertain about their true abilities. They however have beliefs about their abilities which determine effort provision and which are updated based on different sources of information they have received, such as feedback they receive from teachers and parents and their rank in the classroom.

In line with a growing literature that shows the importance of parental beliefs about child skills for parental investments (e.g., Cunha et al., 2013; Boneva and Rauh, 2018; Attanasio et al., 2022; Dizon-Ross, 2019), we show that parents play a crucial mediating role in the significance of rank effects for occupational choices. Students with highly educated parents are less likely to base their choices on classroom rank, in contrast to students whose parents did not pursue any form of tertiary education. Building on findings in Kinsler and Pavan (2021) that show that parental beliefs about child skills are also distorted by relative social comparisons and Dizon-Ross (2019) documenting differences in the abilities to assess child skills by education, we argue that highly educated parents are better equipped to assess their children's abilities and provide targeted support, while less educated parents may rely more heavily on classroom comparisons to gauge their children's abilities.

Second, our analysis, based on tax records spanning from 2012 to 2020, reveals a positive effect of math rank on earnings several years after entering the labor market. Specifically, our estimates indicate that being ranked at the top of the classroom distribution, as opposed to the bottom, is associated with a yearly income increase of more than 3000 *Swiss Francs* (CHF), which is equivalent to a 9.4% rise relative to the sample mean. In line with previous research emphasizing the positive link between the math or STEM intensity of occupations and earnings (Joensen and Nielsen, 2009), we document that these effects are partly mediated by occupational choices, but effort provision can also explain an important part of the effect.

Finally, we show, in line with a higher willingness to provide effort, that students with higher ranks are also more likely to acquire further human capital beyond the initial training program and are more likely to acquire an additional education that can facilitate self-employment. However, our analysis does not reveal any evidence that occupational choices based on rank lead to a greater likelihood of dropping out from the initially chosen occupation or switching to an occupation in a different educational field as a result of occupational choices based on perceived in addition to actual ability.

Our contribution to the literature is threefold. First, we contribute to the extensive literature on the factors influencing educational and occupational choices. Previous studies have extensively examined the impact of post-secondary education on labor market outcomes (Gemci and Wiswall, 2014; Kamhöfer et al., 2018; Altonji et al., 2016). These studies have identified various factors shaping educational choices, such as supply-side factors (Kirkeboen et al., 2016), expected earnings (Wiswall and Zafar, 2015), perceived ability (Arcidiacono, 2004; Arcidiacono et al., 2015), economic conditions (Blom et al., 2021), information (Fricke et al., 2018), parental influence (Zafar, 2013), role models (Kofoed et al., 2019; Porter and Serra, 2020), school curricula (De Philippis, 2021; Strazzeri et al., 2022; Arold, 2024), and peers (Sacerdote, 2001; Giorgi et al., 2012). While considerable attention has been devoted to the major choices of college students, less is known about the educational decisions of students in community colleges and in vocational education programs. As graduates from vocational education programs face greater difficulties in switching occupations compared to graduates from general education, they are more vulnerable to changing labor market conditions (Dauth et al., 2021). Therefore, understanding the initial occupational choices is important as they can have far-reaching consequences for career opportunities (Acton, 2021; Wolter and Ryan, 2011). We study how a naturally occurring feature of the classroom environment -rank in math- shapes occupational choices, made immediately after compulsory schooling.

Second, our study contributes to the expanding literature exploring the effects of peer composition in schools on educational and labor market outcomes. Previous research has demonstrated the influence of various peer characteristics, including gender (Zölitz and Feld, 2021; Bostwick and Weinberg, 2022), disruptiveness (Carrell et al., 2010; Balestra et al., 2022), personality (Golsteyn et al., 2021), and academic achievement (Feld and Zölitz, 2022; Balestra et al., 2023), on educational attainment, major choices, non-cognitive skill development, and earnings. In our paper, we specifically focus on a distinct type of peer effect, which relates to the impact of students' ordinal ranks in the ability distribution within the school environment.[2] The ordinal rank has been shown to influence educational outcomes (Elsner and Isphording, 2017; Murphy and Weinhardt, 2020; Elsner et al., 2021; Delaney and Devereux, 2021; Megalokonomou and Zhang, 2022), labor market earnings (Denning et al., 2023), bullying (Comi et al., 2021), skill development (Pagani et al., 2021), and mental health (Kiessling and Norris, 2023).[3] Our study shares a similar empirical strategy with some previous work, but the focus on occupational choices is different. Furthermore, next to Denning et al. (2023) we are the first study to link earning information from administrative records and we investigate further investments in human capital, which are likely to contribute to a persistence of rank effects, using administrative data. Moreover, we utilize the comprehensive subject-specific survey data from the PISA-2012 tests to demonstrate the importance of effort provision as a mediating channel.

Third, we contribute to the literature on the role of parents in child skill investments (e.g.,

[2] Bertoni and Nisticò (2023) show that neglecting the "rank effects" severely down biases standard linear-in-means peer effects.

[3] For a recent review on rank effects and educational outcomes, see Delaney and Devereux (2022).

Cunha et al., 2006; Cunha and Heckman, 2007; Cunha et al., 2010). Several recent studies show that parental investments are strongly related to heterogeneity in beliefs over child skills with education and social environments playing an important role in shaping beliefs (e.g., Boneva and Rauh, 2018; Attanasio et al., 2022; Dizon-Ross, 2019; Kinsler and Pavan, 2021). We take an important step forward and provide evidence for an additional role that parents play by showing that parents can play an important mediating role in limiting the adverse effects of negative information about their own ability.

The rest of the paper is organized as follows. The next section provides a short explanation of the Swiss (vocational) education system. Section 3 presents information about the data used and the variables of interest, while Section 4 describes the empirical strategy. Sections 5 and 6 present the main results on occupational choices and labor market outcomes. Section 7 concludes.

2 Education system in Switzerland

In the Swiss education system, around 95% of students of compulsory school age attend public schools, free of charge and considered to be of high quality (Nikolai, 2019). After compulsory schooling (K+9), students sort mainly into two different upper secondary education paths.[4] Students who enroll in a fully school-based general education track (baccalaureate schools) typically aim for academic degrees at institutions of higher education (e.g., universities, or universities of applied sciences) (Albiez et al., 2024).

The majority of Swiss adolescents, approximately two-thirds of each student cohort, choose to attend the vocational education and training track (VET). Students select one of over 250 training occupations spanning various sectors and industries. Vocational programs teach students occupation-specific practical and theoretical skills, preparing them for non-academic careers in the labor market. Around 90 % of VET programs consist of a dual training system, i.e., a combination of school and firm training, with students being trained partly at training firms through on-the-job apprenticeships (3-4 days a week) and partly at a vocational school (1-2 weekdays).

The VET system is market-based. Training companies announce apprenticeship openings, students apply for these openings, and firms recruit potential apprentices from the pool of applicants after a selection process. After finishing the training for the chosen occupation, appren-

[4]Around 90 % of students in each cohort continue their education in upper secondary school immediately after compulsory school, and completion rates of upper secondary levels are high, around 91% (SKBF-CSRE, 2011).

tices are awarded a nationally recognized certificate and can start working as qualified workers or continue their education at the tertiary level after the acquisition of a further qualification ("Berufsmatura"). Since very few students change tracks, both within VET programs and between VET programs and general education, the selection of an educational track and a training occupation at the secondary level has far-reaching consequences for career opportunities and is closely connected with future income (Tuor and Backes-Gellner, 2010).

3 Data

3.1 Data sources

For the empirical analysis, we use student-level data from the Program for International Student Assessment (PISA hereafter). The Organization for Economic Co-operation and Development (OECD) has administered this international standardized test since the year 2000 on a three-year cycle, assessing achievements in math, science, and reading of representative random samples of 15-year-old across a diverse array of countries.[5]

In our analysis, we employ the Swiss section of the PISA-2012 wave, consisting of roughly 12 000 9th graders, whose math, science, and reading skills were assessed via pencil-and-paper tests. Besides information on math, science, and reading ability, PISA-2012 collects a comprehensive set of background information on students and schools. Additional survey items assessed students' attitudes, beliefs, and preferences towards math.

The PISA-2012 data is linked to three distinct data sources that allow us to investigate educational and occupational choices, as well as labor market outcomes. First, the PISA-2012 data is matched to the *Längsschnittanalysen im Bildungsbereich data* (LABB hereafter), administrative registry data from the universe of students in Switzerland. Individual identifiers included in the dataset allow us to track educational pathways from 2012 to 2020, students' transition into upper-secondary education and beyond. The LABB dataset entails yearly details on students' ongoing educational status, encompassing factors such as the type and location of educational institutions, school tracks[6], and grades, along with a range of student background characteristics,

[5]For more information on PISA, see https://www.oecd.org/pisa. The population sampling is the result of a two-stage stratified design, where, first, schools are randomly sampled, and second, a randomly selected set of students from each school participate. For a more detailed description of the design and structure of PISA tests see also, e.g., Davoli (2023) or Griselda (2024).

[6]Starting in lower secondary school, students are tracked by their academic ability. Roughly one-third of students

including age, gender, first language, parental education, and migration status. It also contains class identifiers, which we use to define a student's peer group.[7]

Second, we gather information on the cognitive skill requirements of the training occupations, to classify the STEM intensity of occupations. For more details see Section 3.3. We use information from a website, which is managed by the Swiss Trades and Crafts Association (*Schweizerischer Gewerbeverband sgv*) and the Swiss Conference of Cantonal Ministers of Education (EDK), partially funded by the Swiss Secretariat for Education, Research, and Innovation.[8] Skill requirements on four main subjects (math, natural science, language, foreign language), valued on a 1-to-100 scale, are derived from a systematic comparative rating process with input from experts and practitioners in the field, including vocational school teachers and human resource managers from training companies.

Finally, we follow students in the labor market until the year 2020 and match PISA-2012 with administrative information from the Swiss Tax Authority about their employment status and their earning records.

3.2 Sample

From an initial sample of roughly 12 000 students observed in PISA-2012, we derive our final sample imposing two restrictions. First, we include only students for whom we have at least one other student observation in the same classroom in the PISA-2012 data.[9] Second, we exclude student observations that could not be successfully linked to our two administrative data sources, e.g., because students migrated to other countries. The resulting dataset consists of 11 684 9th-grader observations from 1 470 classes of 492 schools. Table 1 reports mean values of student and school characteristics by students' position in the within-classroom math ability distribution. Ability is defined on the base of the PISA-2012 test score result.

Unsurprisingly, we do not find differences in school characteristics between low- and high-ranked students in the classroom. Most students are located in the German and French language

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of each cohort are assigned to a track with basic requirements (low-track) and the other two-thirds attend a track with extended requirements.

[7]The LABB program, an initiative of the Swiss Federal Statistical Office, integrates several sources of education register data. For more information, see https://www.labb.bfs.admin.ch.

[8]For more information, see https://www.anforderungsprofile.ch. The website intends to aid students, as well as those who guide them such as parents and teachers, in selecting a vocational training that aligns with their profile by offering insights into the skills necessary to complete the VET program.

[9]In Section 5.3, we address concerns for the robustness of our results related to this specific sampling restrictions and to the fact that PISA-2012 data do not always include all students in each observed classroom.

regions of Switzerland. Roughly two-thirds of the students enroll in a vocational program after the end of compulsory schooling, consistent with current statistics about education in Switzerland. When looking at students' characteristics by within-classroom math ability, we find that the within-classroom ability distribution is correlated with students' gender and—to a smaller extent—students' migration status, spoken language, parental education, and absolute ability. Female students appear less likely to be part of the math top-performer group, and we observe disparities in migration background, with foreign-born students and students whose mother tongue is not one of the official Swiss languages being more likely to be in a lower position in the within-classroom math ability distribution.

3.3 Outcome variables

We consider four different outcomes as dependent variables: occupational choices, income, human capital investment after compulsory schooling, and dropout from VET programs.

The occupational choices of about 7 000 VET students are assessed using information on the skill requirements of training occupations. We construct a training occupation-specific variable that represents the relative importance of the math and science skill dimension by dividing the sum of both math and natural science skill requirements by the sum of the skill requirements of all four categories. Figure 2 illustrates the distribution of the STEM intensity measure, weighted by the number of trainees in an occupation (bold line, left axis). In our main empirical analysis, we use a binary variable indicating training occupations with a high STEM intensity (i.e., fourth quarter of the stem intensity distribution), but present a set of robustness checks using alternative definitions in Section 5.3.

Income information is obtained through administrative earning records. We sum monthly income from all sources in a given year to obtain a measure of yearly income. The upper part of Table 2 shows mean values of students' income after compulsory school for students who select the vocational education track (first column), general education track (second column), and students who do not continue their education in upper secondary school within the first two years after compulsory school. Table 2 shows that students who select the vocational education track have higher earnings in the years after compulsory school compared to students selecting the general education track since they entered the labor market earlier.[10]

[10] A Swiss franc (CHF) roughly corresponds to one US Dollar.

Finally, we use our detailed student register data to obtain information on students' human capital investments and their likelihood of dropping out of the initial training occupation. Specifically, we calculate the number of years a student is enrolled at a particular educational track. Moreover, for students who started a vocational education program, we can distinguish between education programs that are in the same education field as the initial vocational education program and those that are not. We categorize both the initial vocational education program and further human capital investments in the following education fields based on ISCED codes: Humanities and arts, Social sciences, Business and law, Science, Engineering, Manufacturing and construction, Agriculture, Health and Welfare, Services. Table 3 lists human capital investments after compulsory school for the sample of students who select into a vocational education program. The first column reports the average time spent in post-compulsory education *over the entire sample* for all education fields. The second column reports the same values for education programs in the same field as the initial vocational education program. The third column reports the same values for education programs in different fields as the initial vocational education program. Same field human capital investments are larger even after accounting for the time spent on the initial vocational education program, i.e., looking only at tertiary and professional education.

3.4 Classroom rank

In our empirical analysis, we use students' percentile classroom rank in math to measure students' math rank. We measure math ability by relying on students' performance in the PISA-2012 test. To compute the percentile rank in math R_{ic} of student i in the classroom c, we first determine student i's absolute rank in math in the classroom, n_{ic}, by sorting students by their position in the within-classroom math ability distribution. Students' absolute math rank n_{ic} is a number between 1 and the overall number of students in the classroom (N_{ic}). We assign the absolute rank value of 1 to the student with the lowest ability in the classroom and the highest number (i.e., N_{ic}) to the student with the highest ability in the classroom. Next, we transform the absolute rank in the classroom to the percentile rank using the equation:

$$R_{ic} = \frac{n_{ic} - 1}{N_{ic} - 1}. \tag{1}$$

Independent of class size, R_{ic} assigns value 0 to lowest ability students and value 1 to highest ability students. Figure A1 depicts the variation in ranks based on a student's math ability across the entire sample. On average the ordinal rank rises with a student's ability. However, since our focus lies on estimating the impact of a student's ordinal rank in math while controlling for ability, it's crucial to have ample variation in ranks within each ability level. Figure A1 offers evidence supporting this notion. While the variation of the local rank is strongest in the middle deciles of the math ability distribution and smaller at the upper and lower ends, every decile exhibits significant variations in a student's classroom rank.

4 Empirical approach

To estimate the effect of students' math rank on occupational choices and labor market outcomes, we follow the literature on rank effects (e.g., Elsner and Isphording, 2017; Murphy and Weinhardt, 2020) and compare students who have the same absolute ability but differ with respect to their ordinal rank in the classroom due to different ability distributions of their peers in the classroom.

We rely on the following main specification:

$$y_{ic} = \beta R_{ic} + f(A_{ic}) + \gamma^t X_{ic} + \delta_c + \epsilon_{ic}, \tag{2}$$

where y_{ic} is a measure of occupational choice, labor market outcome, or further education in a given year of student i in the classroom c. R_{ic} is a student i's math rank in classroom c, as defined in Section 3.4, while A_{ic} denotes student i's math ability. $f()$ denotes a flexible functional form of a student's math ability. In our main specification we use a second-order polynomial, but relax this in robustness checks. X_{ic} is a vector of student i's background characteristics (sex, age, parental education, nationality, migration status, language spoken at home), and ϵ_{ic} represents an error term. Additionally, we add a set of classroom fixed-effects, δ_c.

Our coefficient of interest is β, measuring the relationship between the outcome of interest and the ordinal classroom rank in math. To identify the causal effect of students' math rank, the math rank has to be as good as randomly assigned. We rely on the following conditional independence assumption (CIA).

$$E[\epsilon_{ic}|R_{ic}, f(A_{ic}), X_{ic}, \delta_c] = 0 \tag{3}$$

In essence, this assumption implies that ϵ_{ic} is uncorrelated with a student's ordinal math rank given their math ability, personal attributes, and a set of classroom fixed effects. These classroom fixed effects are pivotal for establishing causality, as they encompass all discernible and indiscernible differences between classrooms. We then identify the causal effect of a student's math rank, using combinations of various shapes of the math ability distribution across classrooms and the student's own math ability.

In Figure 1, similar to Murphy and Weinhardt (2020), we visualize the variation in math rank which we rely on in our main specification. The demeaned math test scores are plotted against the math rank measure, displaying how students with identical test scores may end up with very different ranks. This variation exists because classes are small and achievement distributions differ. We complement this analysis in Table A1 where we assess the raw and conditional variation in our treatment variable across different parts of the math ability distribution, showing that the raw variation in ranks without controls amounts to 0.33. The residual variation in ranks after conditioning on classroom fixed effects and control variables leaves around 42% of the raw variation. To ensure that there is enough remaining variation across the entire distribution of the math ability variable, we also show the raw and conditional variation by decile of math ability. Conditioning on classroom fixed effects and our set of baseline controls leaves at least 41% of the raw variation in each decile. Thus, there remains substantial residual variation in ordinal ranks to study their causal effect on occupational choices and further labor market outcomes.

4.1 Identification challenges

4.1.1 Salience of the rank variable

An important question is to what extent students are aware of their ability and know how it compares to that of their classmates. While this might be a particular concern in large peer groups such as school cohorts or schools, it is very plausible that students know about their relative ability in small classrooms such as the ones typical of Swiss schools with on average less than 20 students in a classroom (see Table 1). While we cannot directly test this, or compare PISA results with grades, we do observe evidence supporting the idea that students are aware of their relative ability in the class. As we show more extensively in Section 5.2, students with a higher math rank are also reporting higher self-perceived math ability conditional on their absolute ability, a link that indicates an awareness of their relative ability. Moreover, the main advantage of using a PISA-based rank measure is its comparability across classrooms, its standardized nature, and the fact that it is assessed by external evaluators, reducing the bias of potential alternative metrics such as teacher-assigned grades. A disadvantage of the PISA-2012-based rank measure is that we do not observe the PISA-2012 scores for every student in each class. The validity of the rank measure therefore relies on the random sampling of students in the PISA-2012 test. In Subsection 5.3 we show the robustness of our results to alternative samples based on the number of students missing in the classroom.

4.1.2 Classroom-level confounders

One of the most important concerns regarding the identification of rank effects is that students' ordinal rank is (even under random classroom assignment) cross-sectionally correlated with other features of the classroom.

Even if two students with the same math ability are randomly assigned to different classrooms, the classroom distribution of math ability is correlated with students' math rank. For instance, a student placed in a low-performing class may possess a relatively high rank relative to their ability. Thus, our approach must ensure that our estimates are not confounded by factors that are correlated with rank that also influence student outcomes, such as classroom mean ability (typical linear-in-means peer effects). To achieve this, we compare outcomes among students with the same predetermined math ability but differing ranks due to sampling variation, while controlling for classroom characteristics such as mean and variance. To control for any heterogeneity of a classroom, we use classroom fixed effects following Murphy and Weinhardt (2020), Denning et al. (2023), and Kiessling and Norris (2023). The rationale behind this approach is that classroom fixed effects control for all confounding variables that equally affect all students. Therefore, to isolate rank effects, we rely on the variation of students' ranks within their classroom compared to other classrooms, once all observable and unobservable differences between classrooms have been accounted for.[11]

[11]For a more detailed discussion on the challenges to identify rank effects see Denning et al. (2023).

4.1.3 Balancing test

A further relevant concern in our setting is that we do not have random classroom assignment. To test for students sorting into classrooms and to assess whether the peer composition across classrooms aligns with quasi-random peer assignment, we conduct balancing tests on our variable of interest and other peer-related variables. If the conditional independence assumption holds, predetermined characteristics should exhibit no correlation with rank. In Columns (1) and (2) in Table A2 we regress the classroom rank in math against predetermined student characteristics, along with a second-order polynomial in ability and classroom fixed effects. Columns (3) to (6) perform a similar exercise on other dependent variables (peer average math ability and variation in average peer math ability), which should be quasi-randomly assigned in our setting. The results of this exercise indicate that most characteristics are unrelated to our treatment variable, suggesting a quasi-random assignment of peers. While the indicator for female students appears to be associated with a lower rank in math, this association is, on the one hand, not consistent across other quasi-randomly assigned peer variables, and on the other hand quite small in magnitude. However, to safeguard against potential violations of the CIA we control for all student characteristics in our main specification. In Section 5.3 we show that our specification choice is robust against several alternative specifications.[12]

5 Ordinal rank and occupational choices

We begin our analysis by examining the impact of students' rank in math on the STEM intensity of their chosen occupation. Table 4 presents our findings. The dependent variable is a binary measure denoting the STEM intensity of an occupation. We define an occupation as STEM-intensive if it falls within the upper quartile of the STEM intensity distribution of all occupations, signifying a STEM intensity exceeding 67.37%. All of our results account for classroom fixed effects, individual-level controls, and the absolute ability level of each student, determined by utilizing a second-order polynomial function based on their corresponding PISA-2012 score. Standard errors are clustered at school-by-track level.[13]

[12] Since we use a reduced sample of students selecting into VET program in several specifications we show in Table A3 that the balancing test looks very similar when using the reduced sample of students selecting into VET programs.

[13] Note that a small number of occupations lack these skills measures, and we assess the robustness of our results with respect to these missing observations in Section 5.3.

In Column 1 of Table 4, we observe that a student's classroom rank in math significantly influences the likelihood of selecting a STEM-intensive occupation, conditional on the absolute math ability. Our estimation results indicate that being ranked at the top of the classroom, compared to the bottom, is associated with a 9.2 percentage point increase in the likelihood of choosing a STEM-intensive occupation (a 40% increase relative to the sample mean). An alternative interpretation of this finding is that a 1 standard deviation increase in math classroom rank corresponds to a 3 percentage point rise in the likelihood of choosing a STEM-intensive occupation, equivalent to a 14% increase relative to the sample mean (see Table A4).

To demonstrate the relevance of our findings to students' subject-specific classroom rank in math, as opposed to a general classroom rank, we present results using students' reading and science rank as treatment variables in Columns 2 and 3. Notably, the estimates for classroom rank in science and reading do not carry economic significance and are not significantly different from zero.

A concern regarding our results is their applicability only to those who opt for a vocational educational program, as our measures for the skill intensity of chosen occupations are available exclusively for these students. To address the concern that our results might be influenced by students' selection across different educational tracks, we expand our analysis to include a thorough examination of students' educational choices after compulsory schooling. Table 5 presents our estimation results related to the educational choices made immediately after students complete compulsory schooling. In particular, the dependent variable is set to 1 if a student pursues one of the following paths within a year after finishing compulsory education: a vocational education track (Panel A), a general education track (Panel B), or whether they do not enroll in upper secondary school (Panel C).

The estimates in Column 1 suggest that, after accounting for absolute math proficiency, students with higher math rankings are slightly more inclined to opt for a vocational education track after completing compulsory school (Panel A). Conversely, they are less likely to enroll in a general education program (Panel B) or to forgo any further educational program (Panel C). These results maintain their qualitative consistency when we control for all rank measures simultaneously (as shown in Column 4). However, none of these estimates significantly deviate from zero. Therefore, we conclude that selection effects into different educational tracks, driven by classroom rank in math, do not appear to be a concern when analyzing student outcomes separately based on their initial track choice.[14]

5.1 Heterogeneity

In this subsection, we investigate non-linearities and effect heterogeneity. After investigating whether the classroom rank has a non-linear impact on occupational choices, we focus on three student characteristics to investigate effect heterogeneity based on the related literature – ability, gender, parental background –. Understanding effect heterogeneity of rank effects is particularly important since, different from standard linear-in-means peer effects, there can be improvement in overall outcomes be reassigning students across classes (Denning et al., 2023).

We start by investigating heterogeneity with regard to the relative position in the classroom. In our main specification, we use a linear estimation procedure. While some studies have found limited evidence for nonlinear effects (Delaney and Devereux, 2021), several studies have suggested that rank effects may not necessarily follow a linear pattern (e.g., Gill et al., 2019; Denning et al., 2023; Megalokonomou and Zhang, 2022). To explore the potential presence of nonlinear effects in the context of occupational choices, we extend our analysis by replacing the linear subject rank variables with indicators for each tercile of the rank distributions, using the second tercile as the reference category. The results, shown in Table 6, indeed indicate the presence of nonlinear effects. While there appears to be a penalty for ranking in the bottom tercile compared to the mid-tercile, the relationship remains relatively flat in the upper part of the rank distribution.

In addition to studying non-linear rank effects, we also investigate effect heterogeneity with regard to students' math ability. In Panel A of Table 7 we show that students with above and below median math ability are not differently affected by their classroom rank.[15]

Extensive research has uncovered distinct behavioral patterns between boys and girls. Some of these findings, relevant to our study, reveal that girls often exhibit lower levels of competitiveness compared to boys (Buser et al., 2017) and tend to demonstrate lower levels of confidence in math-related subjects (Bordalo et al., 2019). Additionally, multiple studies have pointed out

[14]For the sake of completeness, we also provide results based on science rank (Column 2) and reading rank (Column 3). However, similar to math rank, we do not observe any meaningful selection effects in educational tracks related to students' science and reading rank.

[15]We investigate this question in more depth by splitting the data into quintiles of the math ability distribution. We present the results in Figure A2. We also observe little evidence for effect heterogeneity. Point estimates are rather constant across the four bottom quintiles and only in the top quintile do we observe a slightly smaller point estimate.

the significant under-representation of female students in STEM occupations (e.g. Cimpian et al., 2020; Goulas et al., 2022). This pattern is similar in Switzerland. Figure 2 shows the corresponding percentage value of female trainees in the occupation (right axis). The bimodal density function in Figure 2 shows that female vocational education students are more likely to select occupations with lower STEM intensity. To discern gender-specific effects more precisely, we introduce interaction terms between math rankings and a gender indicator. The results are presented in Panel B of Table 7. Our analysis does not reveal any significant evidence for a differential response to classroom rank in math between boys and girls.

Next, we explore whether parental education influences the role of ranks in shaping occupational choices. Parents play a crucial role in shaping their children's educational investments (Cunha et al., 2013; Figlio et al., 2019; Kinsler and Pavan, 2021; Cobb-Clark et al., 2021; Attanasio et al., 2022) and occupational choices (Bennedsen et al., 2007; Bell et al., 2019). One way parents may impact their children's educational choices is by forming beliefs about their abilities and providing useful feedback and guidance toward educational investments. Research has suggested that less-educated parents may have less accurate beliefs compared to well-educated parents because they may find it challenging to assess their children's performance themselves, leading them to rely more heavily on comparisons within the classroom (Dizon-Ross, 2019; Kinsler and Pavan, 2021). Our findings support this notion. In Panel C of Table 7, we demonstrate that children of college-educated parents are significantly less inclined to make rank-based occupational choices compared to children whose parents did not attend college.

5.2 Mechanisms

We now turn towards understanding the mechanisms behind our results. The previous literature has shown that besides its effect through changes in teacher and parental investments, changes in students' beliefs and behavior are the main mechanism that explains students' outcomes due to classroom rank (Murphy and Weinhardt, 2020; Elsner and Isphording, 2017). To assess the relationship between classroom rank in math and students' beliefs and behavior, we leverage detailed information on math attitudes and beliefs from the PISA-2012 questionnaire. Specifically, we examine students' responses to eight categories of questions concerning their attitudes toward math, their willingness to exert effort in math, and their direct classroom environment.

Students' responses are measured on a 4-point Likert scale.[16]

Table 8 summarizes our estimation results concerning students' attitudes toward math. We observe that classroom rank in math is positively linked to several aspects. In Columns 5 and 7, we show a strong positive association between classroom rank in math and students' perceived ability, which aligns with our initial argument that perceived ability, in addition to actual ability, significantly influences occupational choices. This finding is also consistent with previous research indicating that classroom rank has a lasting impact on confidence (Murphy and Weinhardt, 2020; Elsner et al., 2021).

Furthermore, we identify a strong positive association between math rank and students' interest in math, as well as students' willingness to put effort into the subject (as shown in Columns 1 and 8). The positive association between subject-specific ranks and effort is in line with theoretical consideration in which perceived ability determines effort provision (Kiessling and Norris, 2023). Interestingly, our analysis does not reveal a significant relationship between classroom rank in math and the selection of a particular peer group (as presented in Column 3).

5.3 Robustness checks

In Section 5, our analysis is limited to VET students for whom we observed the math intensity of their chosen occupation. Students for whom we lacked information about the skill requirements of their chosen occupations were excluded from the sample. In Table A6 and Table A7, we demonstrate that these missing observations do not substantially impact the interpretation of our results. We achieve this by either assigning the missing values a 0 math intensity measure (Table A6) or a 1 math intensity measure (Table A7). Our findings remain robust to these specifications.

Another potential concern is that our results may depend on the specific definition of a STEM occupation we used. We address this concern in Table A8 by constructing three alternative outcome variables. First, we use the math intensity of an occupation as a continuous measure (Panel A). When employing the percentage value of math and science requirements among all requirements for each occupation as a continuous STEM intensity measure (Panel A), we find that ranking at the top of the classroom, compared to ranking at the bottom, increases the likelihood of

[16] A complete list of the questions can be found in Table A5. Questions are aggregated into eight categories following PISA-2012 Technical report.

selecting an occupation with higher math and science requirements (STEM) by approximately 2.1 percentage points (or 3.5% relative to the sample mean). Second, we define an occupation as a STEM occupation if it falls within the 90th percentile of the STEM intensity distribution (Panel B). Third, we define an occupation as a STEM occupation if it belongs to the 50th percentile of the math distribution (Panel C). Importantly, we observe a positive and significant effect of math rank on STEM choices, even when defining a STEM occupation as within the 90th percentile. Furthermore, as sort of a plausibility check we show that the effect is substantially smaller when using a broad definition of a STEM occupation (Panel C).

Moreover, we address concerns related to the specific sampling procedure used in the PISA-2012 data. The PISA data does not always include all students in each observed classroom. Therefore, our rank measure is constructed using information on all students in a classroom in some cases, while in other cases, it relies on a random sample of students. In Figure A3, we address this concern by examining how our results depend on the sample size of classes included in our estimation. We plot the coefficients for different sample sizes and indicate the sample size corresponding to each sample restriction. The first coefficient on the left shows the results when our sample only consists of classes for which the PISA-2012 sample includes the full class. As we move to the right, we show results with increasing sample sizes, sequentially adding classes for which an increasing subset of students is not sampled. The solid line in the plot represents the corresponding sample size. Our findings indicate that starting from a relatively moderate sample size of around 1000 students, which includes only classes for which we observe at least 90% of the students, we observe a positive and relatively stable effect of classroom rank in math on STEM-intensive occupations. Therefore, our results are unlikely to be significantly affected by the sampling procedure.

Against our assumption that the rank is as good as randomly assigned, parents may select schools based on the rank they expect from their children. In Table A3 we show that our rank measure is uncorrelated with several student background characteristics including parental education and a proxy for socioeconomic status, but we cannot completely rule out other unobserved parental background characteristics to be correlated with our treatment variable. We think that this is unlikely to be an issue, as there is evidence that parents prefer sending their children to schools with high-ability peers (Beuermann et al., 2022). If this is the case, then this is not consistent with positive sorting based on ranks, as ranks and peer ability are inversely related.

Another potential concern might be that in our main specification, we do not account for the possibility of heterogeneous effects of the classroom distribution by prior ability (Booij et al., 2017; Denning et al., 2023). We assume that rank, human capital, and classroom effects are additively separable. If this functional form is misspecified, it may cause rank to be correlated with omitted factors. In other words, classroom fixed effects only capture classroom features that affect all students equally, such as linear-in-means peer effects. If there are heterogeneous effects of the classroom by ability that are correlated with rank, they need to be accounted for. To address this concern, we relax the additive separability assumption by allowing for interactions of classroom characteristics and ability. We categorize distributions of student achievement into groups based on distribution characteristics (i.e., mean and variance) and interact indicators for these groups with our control variables for a student's math ability. In Table A9 we show that our results are robust to the inclusion of these interactions, despite losing some precision.

A final concern might be the existence of a specification error, due to our arbitrary choice of adopting a second-order polynomial to take the relation of occupational choice and ability into account. To ensure the robustness of our results, we explore various alternative specifications in Table A10, changing the way we map ability to occupational choices. Our primary specification controls for absolute math ability using a second-order polynomial. However, we test the robustness of this approach by considering several alternatives. In Columns 2 and 3, we present results based on third and fourth-order polynomials for controlling math ability. Additionally, we examine non-linear approaches by introducing binary variables representing different quantiles of the ability distribution in Columns 4 and 5. Importantly, our results remain consistent across these various ways of controlling for students' math ability, indicating robustness to different specifications.

6 Ordinal rank and long-term outcomes

In this section, we investigate whether the classroom rank in math yields lasting impacts on individual long-term outcomes, beyond the influence on occupational choices shown in the previous section. First, we investigate the association between classroom rank in math and earnings in the years following compulsory education (Section 6.1). Second, in Section 6.2, we focus on investments in human capital as another crucial determinant of labor market success. Finally, in Section

6.3, we investigate the potential negative implications of rank-based decisions for dropout.

6.1 Earnings

Figure 3 provides a summary of our estimation results using yearly income as the dependent variable. Each dot in Figure 3 represents β coefficients from separate estimations of Equation 2 across different income years. Vertical lines denote the 90% confidence intervals computed using clustered standard errors at the school-by-track level. Figure 3a presents results estimated on the sample of students who choose a vocational education training program. For completeness, Figure 3b displays results for the non-VET sub-sample, while Figure 3c presents the results on the full sample.

In Figure 3a, we observe a positive impact of our rank measure on yearly income from 2015 onward. For perspective, in 2020, a student ranking at the top of the classroom in math experiences a yearly income increase of 3,221 CHF- an equivalent to a 9.4% increment relative to the sample mean compared to an equally skilled student at the bottom of the distribution. The absence of an impact of classroom rank on income in the initial three years following compulsory schooling is consistent with the Swiss vocational education system being characterized by relatively modest wage differentials both between and within occupations. Instead, our results indicate that the positive impact of classroom rank becomes evident only after students graduate from a vocational education program and begin to enter the regular labor market.

Figure 3c, displaying estimation results for the full sample, depicts a very similar trend in our estimated coefficient. The confidence intervals become narrower due to the larger sample size, yet the point estimates remain highly consistent. This outcome is in line with the notion that students not pursuing vocational education programs (VET), and opting for general educational programs instead, spend more time in the upper-secondary education level, and are more likely to afterward transition to university education. As a result, the vast majority of this group does not enter the labor market before 2020. Figure 3b illustrates the resulting lack of association between our treatment and earnings for the non-VET students sub-sample.

Panel A of Table 9 summarizes our estimation results on overall income across the entire span of our data set. Panel B of Table 9 reports estimation results on overall income specifically for the years post-graduation from the vocational education program. These estimates, hardly differing from Panel A, corroborate the finding that classroom rank in math affects students' subsequent earnings. In Panel B, our estimate suggests that ranking at the top of the classroom in comparison to the bottom increases income by more than 15 000 Swiss francs or roughly 3 000 francs per year, on average, excluding the years students are enrolled in a vocational education program.

The finding that classroom rank in math is associated with higher earnings is in line with previous findings by Denning et al. (2023) for the U.S. The results in Section 5 suggest that STEM choices, due to their high returns, may be an important mechanism behind this effect. Therefore, we ask, what the share of the income effect is that can be explained by STEM choices. [17]

To quantify the extent to which STEM choices (and other mediators) contribute to the observed income effect we run a mediation analysis in the spirit of Gelbach (2016).[18] We operationalize the decomposition by estimating the following set of equations similar to Equation 2 in which m is the mediator (e.g. STEM choice) and y is the income.

$$y_{ic} = \beta^y R_{ic} + f(A_{ic}) + \gamma^t X_{ic} + \delta_c + \epsilon_{ic}, \tag{4}$$

$$m_{ic} = \beta^m R_{ic} + f(A_{ic}) + \gamma^t X_{ic} + \delta_c + \epsilon_{ic}, \tag{5}$$

$$y_{ic} = \alpha^m m_{ic} + \beta R_{ic} + f(A_{ic}) + \gamma^t X_{ic} + \delta_c + \epsilon_{ic}, \tag{6}$$

We then calculate the corresponding share of the income effect that is explained by the STEM choices in the following way: $\beta^m \alpha^m / \beta^y$. The results are summarized in Table 10. STEM choices explain about 15% of the observed income effect. We then also consider attitudes towards math as potential alternative mediators in line with our analysis in Section 5.2. We find that perceived ability in math, interest in math, and willingness to provide effort in math predominantly explain meaningful shares of the income effect. We provide complementary results in which we consider occupational choice as an outcome variable and attitudes towards math as potential mediators (Table 11). While interest in math and perceived ability in math explain above 10% of the observed

[17] In results not shown in this paper we looked at the probability of being unemployed and the duration of unemployment as further potential labor market outcomes. We do not find an association between our treatment and both unemployment measures.

[18] The results of the mediation analysis only reflect causal estimates under very strong assumptions. However, they present the best approximation possible for the importance of STEM choices as a mediator in comparison to other channels.

effect on STEM choices, willingness to provide effort in math is way less relevant for STEM choices, rather than the observed income effect.

6.2 Human capital investments

In this section, we explore whether classroom rank in math is associated with another crucial determinant of labor market success—investments in human capital after compulsory schooling. Prior research has highlighted the role of human capital investments in shaping labor market outcomes (e.g., Ruhose et al. (2019)). We examine whether students with higher ranks further increase their human capital beyond the first chosen VET program. Table 12 presents estimation results employing the number of years a student invests in a particular education program post-compulsory schooling as the outcome variable in our baseline specification.

Panel A of Table 12 reveals that students ranking at the top of their class, in contrast to their peers at the bottom, exhibit an average increase of around 0.25 years in additional human capital investment. To gain further insights into the nature of these investments, we create several subcategories and separately examine whether the results are driven by additional time spent in colleges, vocational education programs, or professional education. We also distinguish between investments in the same educational field as the student's initial VET program (Panel B) and investments in different fields of education (Panel C).

While we do not observe an increase in the time allocated to college education, we do observe an increase in the time spent in vocational education. A potential concern regarding the interpretation of this result is that these findings may reflect delayed graduation rather than additional investments in further education. However, this is unlikely to be the case, as we observe that the additional investment stems from programs in different occupations within the same educational field (Panel B).[19] Furthermore, we find that students are more likely to invest in professional education, often a meaningful step towards self-employment (Panel B).

6.3 Dropout

In Section 5, we establish that classroom rank in math exerts a causal influence on the math intensity of occupational choices, with perceived ability being a probable mediator of this impact.

[19] A concern might be that this reflects dropout from initial training programs. We address this question in more detail in Section 6.3

A valid concern about this effect is that choices founded on perceived ability, rather than actual ability, may not be efficient. Students making decisions based on perceived ability may experience discomfort with their chosen occupations, leading to a higher risk of failure or dropout. In line with this argument, Hastings et al. (2016) finds that well-informed college choices significantly impact persistence and graduation rates. To explore this issue, we investigate whether classroom rank in math has negative consequences for persistence rates within the chosen occupation.

We employ two measures of occupational persistence. First, we examine the time spent within occupations in educational fields different from the student's initial occupation choice. Second, we employ a binary measure indicating dropout from the chosen vocational education and training (VET) program. In Panel C of Table 12, we present our findings on the time spent in training occupations across different educational fields. Our results indicate that classroom rank in math is not associated with a general increase in the time spent in any type of educational program. While all coefficients are negative, they fail to achieve statistical significance. Additionally, in Table 13, we show that classroom rank in math does not have a positive causal effect on the likelihood of dropping out from the initially chosen VET program.

In summary, these analyses do not provide compelling evidence that occupational choices influenced by perceived ability, rather than actual ability, result in dropout from the initial occupational choice. The finding does not imply that the observed matches between students and occupations are necessarily efficient. In fact, the impact of rank on the willingness to provide subject-specific effort might offsets the potential negative consequences of decisions based on perceived ability.

7 Conclusion

This paper investigates the influence of students' classroom rank in math on their occupational choices and long-term educational and labor market outcomes. Ordinal rankings are an inherent feature of social environments, and math ability is of well-accepted importance for individual and societal outcomes (Hanushek et al., 2015). Thus, understanding the consequences of relative math ability on critical life decisions is crucial.

We provide compelling evidence about three sets of results. First, higher classroom ranks in math, conditional on ability, increase the likelihood of selecting a STEM-intensive occupation. To shed light on the mechanisms behind this effect, we show that classroom rank in math is positively associated with perceived math ability and the willingness to study math. This finding is consistent with the idea that students are uncertain about their true ability. Receiving information about their math ability, for example via their rank in the classroom, they update their beliefs about their own math ability which may result in changes in their willingness to provide subject-specific effort (Kiessling and Norris, 2023).

Furthermore, we find that parental education serves as a mitigating factor in the impact of ranks on students' occupational choices. We show that students from highly educated parents are significantly less likely to make rank-based occupational choices compared to students with less educated parents. We argue that parental feedback is a complementary source of information students receive about their ability (Dizon-Ross, 2019). While students with highly educated parents may receive more accurate feedback to help assess their own ability, the opposite is true for students with less educated parents, who are relying more intensely on rank-based information. This finding also has important practical implications. Unlike linear-in-means peer effects, where moving students between classes has no net impact, grouping students by rank and taking the observed heterogeneous effects into account could improve labor market outcomes, and lower entry barriers in high paying or selective occupations.

Second, we show that occupational choices have lasting consequences in the labor market, as students with a higher math classroom rank substantially outperform their peers' income several years after completing compulsory schooling. A noticeable share of this effect is mediated by occupational choices. However, our analysis suggests that an increased willingness to provide effort can also explain a substantial share of the income effect.

Finally, we provide evidence that a higher classroom rank in math translates into larger investments in educational programs after compulsory education, while we do not find evidence for increased dropout rates from training occupations. This may be attributed to the increased effort exerted by students.

Our study underscores the importance of considering social dynamics within educational settings when evaluating students' career decisions and encourages further research in at least two ways. First, it stresses the importance of research investigating how to overcome rank-based occupational choices. Giving information about global ranks could be beneficial to offset the negative effects of low-rank effects that only arise due to small section comparisons. Second, it points towards the importance of understanding the consequences of relative feedback mechanisms on educational investment decisions.

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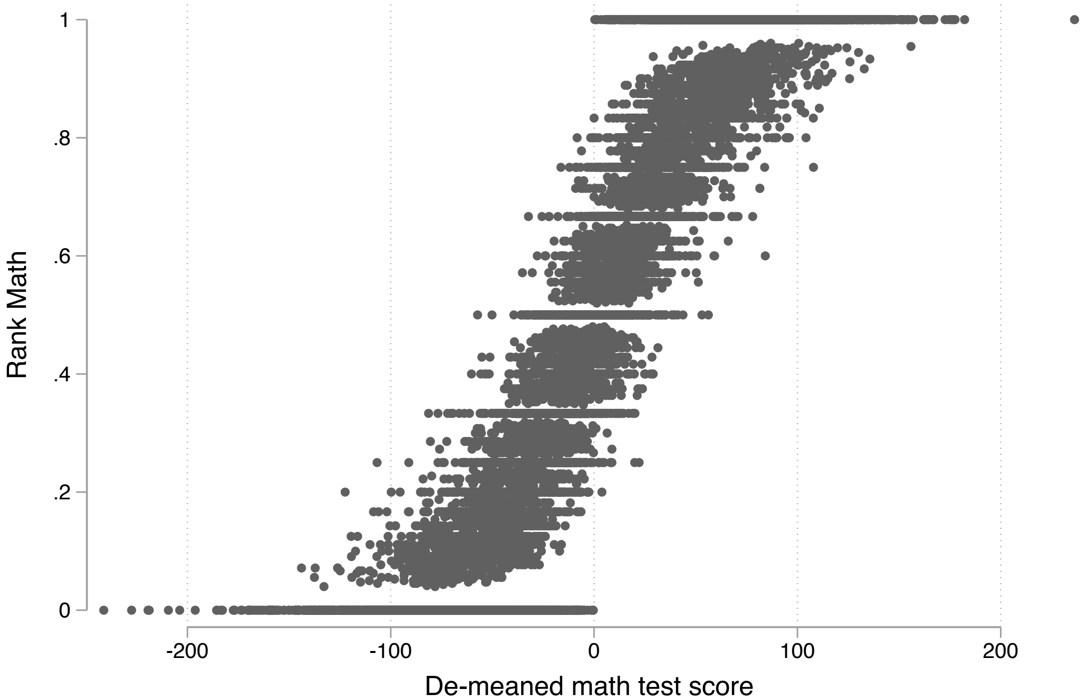
TABLES AND FIGURES

Figure 1:
Distribution of rank measure across classrooms



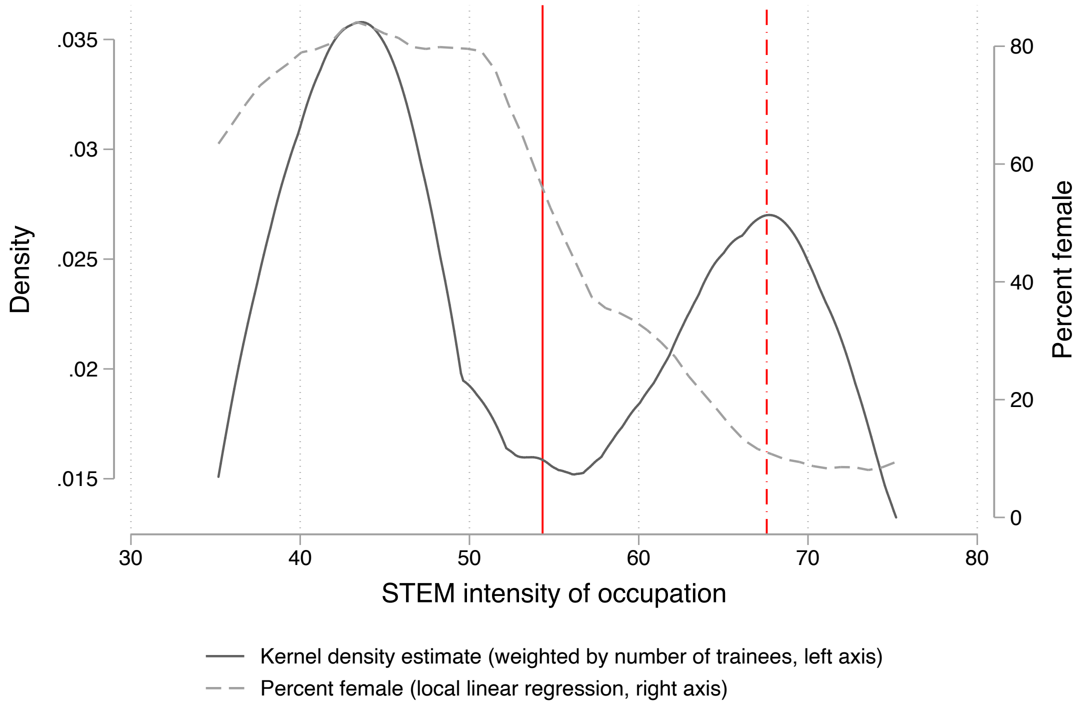
Note: Scatter plot of percentile rank measure in math (on the Y-axis) and de-meaned classroom-level math test scores in math (on the X-axis).

Table 1:
Summary statistics of background characteristics

	Bottom 50 %	Top 50 %	t-value
Student characterisitcs			
Age	15.9	15.7	-12.65
Female (%)	59.7	42.2	-19.15
Migration status (%)			
Swiss born in CH	76.5	83.1	8.86
Non-Swiss born in CH	13.1	8.8	-7.50
Swiss not born in CH	3.1	2.6	-1.59
Non-Swiss not born in CH	7.3	5.6	-3.72
First language: language of CH (%)	80.2	86.7	9.47
At least one parent attended college (%)	54.6	57.5	3.18
Books at home (%)			
0-10	17.8	11.1	-10.31
11-25	17.7	13.3	-6.62
26-100	30.5	29.3	-1.45
101-200	16.4	20.3	5.55
201-500	10.0	15.6	9.05
More than 500	5.9	9.1	6.60
PISA-2012 score			
Math	486.7	568.8	62.33
Reading	477.6	534.4	41.04
Science	475.0	541.3	50.65
Rank Math (0-1)	0.214	0.786	185.83
9th grade school characteristics			
Location: population density (%)			
Urban area	52.9	51.8	-1.29
Intermediate area	25.6	25.4	-0.27
Rural area	21.0	22.3	1.69
Location: language region (%)			
German	51.2	51.3	0.09
French	47.4	47.2	-0.16
Italian	0.8	0.8	-0.02
Rhaeto-Romance	0.1	0.1	-0.91
School track (%)			
Low-track	21.2	20.9	-0.38
High-track	66.0	66.1	0.11
Mixed-track	12.8	13.0	0.31
Class size	19.2	19.3	0.30
Class size (PISA-2012 sample)	5.8	5.8	-0.79
Track choice after 9th grade (%)			
VE program	62.2	61.5	-0.81
GE program	30	33	4.41
No program	8	5	-6.65
Number of observations	5,853	5,831	

Note: Mean values of student and school characteristics and students' track choices after 9th grade for students below and above the median math ability of their classroom. Students whose math ability equals the median math ability of the classroom are randomly allocated to one of the two groups. The last column reports t-values of a two-sided t-test comparing both groups of students.

Figure 2:
STEM intensity of training occupation and female share



Note: Figure illustrates the STEM intensity of training occupations of students who select into a vocational education program after compulsory school (left axis) and the percentage value of female students in the corresponding training occupation (right axis). The solid vertical line indicates the sample mean of the STEM-intensity distribution (weighted by number of trainees) of 54.32. The dash-dotted vertical line indicates the 75th percentile of the unweighted STEM-intensity distribution at 67.56. 20.44 % of students who select into a vocational education program start a training occupation that lies above the 75th percentile of the unweighted STEM-intensity distribution.

Table 2:
Summary statistics of outcomes after compulsory school

	VE students	GE students	Others
Overall	198,232	52,112	108,840
By year			
2012	40	1	3
2013	1,155	48	600
2014	7,835	664	3,919
2015	15,351	2,422	6,974
2016	23,726	4,693	9,793
2017	30,680	6,349	14,331
2018	35,966	8,280	20,421
2019	39,940	11,869	24,963
2020	43,538	17,786	27,838
Dropout from VET			
Dropout	0.16	–	–
Observations	7,229	3,682	773

Note: Mean values of students' income after compulsory school by track-choice (overall income in the observation period and income by year) and mean value of dropout probability from the initial VET program.

Table 3:
Summary statistics of outcomes after compulsory school, vocational education students

	All fields	Same education field	Other education field
Vocational education			
Years enrolled	3.69	3.41	0.27
Same occupation			
Years enrolled	2.89	2.89	0.00
Different occupation			
Years enrolled	0.80	0.53	0.27
Professional education			
Years enrolled	0.31	0.25	0.06
College			
Years enrolled	0.52	0.34	0.18

Note: Mean values of educational choices by field of education relative to the field of education of the initial training occupation. Sample consists of students who start a vocational education program (N=7,229).

Table 4:
Result: Effect on selecting a STEM occupation

	(1)	(2)	(3)	(4)
Rank Math	0.092**			0.089**
	(0.041)			(0.043)
Rank Reading		0.015		-0.003
		(0.039)		(0.042)
Rank Science			0.022	-0.026
			(0.041)	(0.045)
Controls	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes
Observation	6,580	6,580	6,580	6,580
Cluster	480	480	480	480

Note: Each column reports estimates of separate regressions of a variable indicating the STEM intensity of the first training occupation (in percent, Panel A) or a binary variable indicating if the STEM intensity of a students' first training occupation lies in the 4th quarter of the STEM intensity distribution of all training occupations (Panel B) on students classroom rank in math and/or science and/or reading (0-1, based on PISA-2012 scores) in the last year of compulsory school. Sample is restricted to students who start a vocational training program within one year after graduating from compulsory school. Control variables: gender, date of birth (month-times-year dummies), parental education (college education, binary), number of books at home (7 categories), migration status (4 categories), language spoken at home (official language of CH, binary), PISA-2012 test score (and squared term) in math (columns 1, 4), reading (columns 2, 4), science (columns 3, 4). Robust standard errors are clustered at school-times-track level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 5:
Effect on track choice

	(1)	(2)	(3)	(4)
A: Start VE program				
Rank Math	0.039			0.034
	(0.024)			(0.028)
Rank Reading		0.027		0.022
		(0.025)		(0.027)
Rank Science			0.012	-0.008
			(0.025)	(0.029)
B: Start GE program				
Rank Math	-0.019			-0.008
	(0.020)			(0.024)
Rank Reading		-0.039*		-0.033
		(0.022)		(0.023)
Rank Science			-0.023	-0.010
			(0.022)	(0.025)
C: Start No program				
Rank Math	-0.020			-0.026
	(0.018)			(0.020)
Rank Reading		0.012		0.011
		(0.018)		(0.019)
Rank Science			0.011	0.017
			(0.018)	(0.022)
Controls	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes
Observation	11,684	11,684	11,684	11,684
Cluster	492	492	492	492

Note: Each column reports estimates of separate regressions of a binary variable indicating whether a student enters a vocational education program (Panal A) or a general education program (Panel B) or no program (Panel C) within one year after compulsory school on students' classroom rank in math and/or reading and/or science (0-1, based on PISA-2012 scores) in the last year of compulsory school. Control variables: gender, date of birth (month-times-year dummies), parental education (college education, binary), number of books at home (7 categories), migration status (4 categories), language spoken at home (official language of CH, binary), PISA-2012 test score (and squared term) in math (columns 1, 4), reading (columns 2, 4), science (columns 3, 4) . Robust standard errors are clustered at school-times-track level.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 6:
Main result: non-linear effects

	STEM occupation
	(1)
Rank Math in first tertile	-0.045***
	(0.016)
Rank Math in third tertile	0.019
	(0.018)
Controls	Yes
Class FE	Yes
Observation	6,580
Cluster	480

Note: The table reports estimates for the model in Equation 2, with rank entering as a set of indicators for each tercile of the rank distributions. The second tercile is the reference category. We include individual level controls as specified in Equation 2 and classroom fixed effects. Robust standard errors are clustered at school-times-track level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 7:
Results heterogeneity

	STEM occupation
	(1)
A: By ability	
Rank Math	0.078*
	(0.045)
Rank Math x Ability	0.026
	(0.032)
B: By gender	
Rank Math	0.088*
	(0.046)
Rank Math x Female	0.007
	(0.035)
C: By parental education	
Rank Math	0.133***
	(0.044)
Rank Math x College educated parents	-0.086**
	(0.034)
Controls	
Class FE	
Observation	6,580
Cluster	480

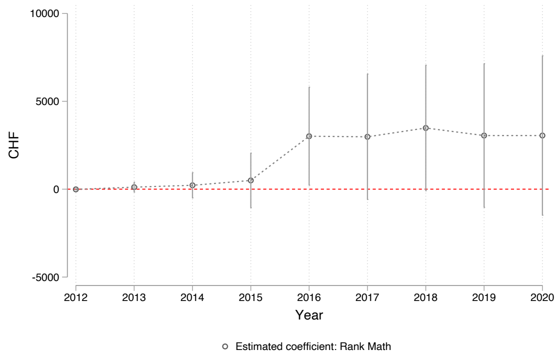
Note: "Ability" is the PISA-2012 math test score; "College educated parents" is an indicator variable for students whose parents have achieved at least college education. We include individual level controls as specified in Equation 2 and classroom fixed effects. Robust standard errors are clustered at school-times-track level.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 8:
Result: Effect on math attitudes

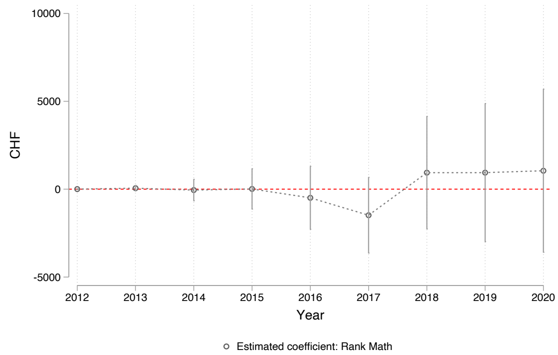
	Interest in math	Math useful in future	Peers interested in math	Confident to be able to solve math problems	Good at math	Anxious about math	Perceived control at math	Provide effort in math
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A								
Rank Math	0.257^{***}	0.080	0.034	0.066	0.241^{***}	-0.093	0.098^{**}	0.126^{**}
	(0.074)	(0.078)	(0.041)	(0.046)	(0.069)	(0.061)	(0.048)	(0.057)
Panel B								
Rank Reading	-0.020	-0.033	-0.040	0.023	-0.012	0.005	0.081^{*}	-0.060
	(0.075)	(0.076)	(0.041)	(0.048)	(0.072)	(0.064)	(0.045)	(0.058)
Panel C								
Rank Science	0.089	0.016	-0.001	0.006	0.063	0.013	0.028	0.048
	(0.076)	(0.076)	(0.041)	(0.048)	(0.070)	(0.062)	(0.046)	(0.060)
Panel D								
Rank Math	0.204^{***}	0.036	0.024	0.023	0.161^{**}	-0.079	0.094^{*}	0.122^{**}
	(0.077)	(0.082)	(0.043)	(0.049)	(0.073)	(0.065)	(0.053)	(0.060)
Rank Reading	-0.040	-0.019	-0.036	0.046	-0.018	-0.006	0.070	-0.090
	(0.073)	(0.076)	(0.041)	(0.045)	(0.067)	(0.061)	(0.048)	(0.059)
Rank Science	0.046	0.029	0.003	0.011	0.016	0.034	-0.006	0.037
	(0.077)	(0.077)	(0.043)	(0.046)	(0.070)	(0.064)	(0.051)	(0.062)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean dependent variable	2.29	2.86	2.67	3.18	2.55	2.21	3.09	2.78
Observation	7,603	7,624	7,439	7,616	7,428	7,561	7,544	7,487
Cluster	490	490	490	491	491	491	491	490

Note: Each column reports estimates of a separate regression of measure of math attitudes (measured between 1-4, not at all to very much) on students' classroom rank in math (Panel A), reading (Panel B), science (Panel C), or all 3 together (Panel D). Control variables: Gender, parental education, age, nationality, migration status, first language spoken at home, type of residence permit. Panel A and D include additional control variables for students' PISA-2012 math test score (and squared term). Panel B and D include additional control variables for students' PISA-2012 reading test score (and squared term). Panel C and D include additional control variables for students' PISA-2012 science test score (and squared term). Robust standard errors clustered at school-times-track-level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

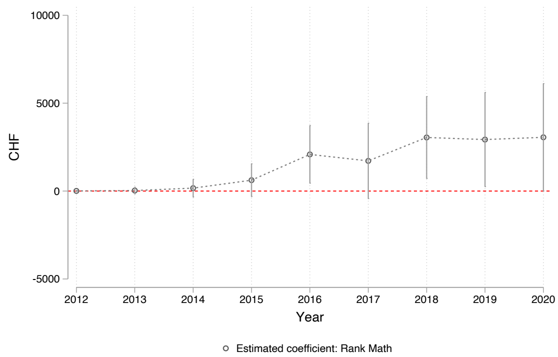
Figure 3:
Results: Effect on income



(a) VE students



(b) Others



(c) All

Note: Each dot illustrates the coefficient estimate of classroom rank in math of separate regressions using yearly income as outcome variable for the entire sample (11'684 observations) and students who started a vocational education program at least one year after compulsory school (7'229 observations). Classroom fixed effects, control variables and PISA-2012 math score (and squared term) included. Standard errors are clustered at school-times-track level. Vertical lines indicate 90 %-confidence interval.

Table 9:
Result: Effect on overall earnings

	Subsample		
	VE students	Others	All
	(1)	(2)	(3)
A: Earnings 2012-2020			
Rank Math	16406.749*	985.949	13671.257**
	(9791.954)	(8810.976)	(6456.875)
B: Earnings 2016-2020			
Rank Math	15580.764*	958.628	12843.325**
	(9112.974)	(8212.156)	(6009.248)
Controls	Yes	Yes	Yes
Class FE	Yes	Yes	Yes
Observation	7,229	4,455	11,684
Cluster	483	421	492

Note: Each column reports estimates of separate regressions of earnings in 2012-2020 (Panel A) or in 2016-2020 (Panel B) on students' classroom rank in math in the last year of compulsory school. Control variables: gender, date of birth (month-times-year dummies), parental education (college education, binary), number of books at home (7 categories), migration status (4 categories), language spoken at home (official language of CH, binary), PISA-2012 test score (and squared term) in math. Robust standard errors are clustered at school-times-track level.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 10:
The importance of mediating factors for income effects

	Share of rank effect mediated (%)	N
Panel A		
STEM choice	15.01	6580
Panel B		
Interest in math	6.44	4683
Math useful in future	–	4691
Peers interested in math	–	4576
Confident to be able to solve math problems	3.00	4693
Good at math	31.10	4585
Anxious about math	3.64	4671
Perceived control at math	–	4643
Provide effort in math	13.52	4598

Note: This table shows the decomposition of the income effect by each related mechanism variable. In Panel A we present the mediating role of STEM choices, whereas in Panel B we focus on the mediating role self-belief and attitudes towards math. Shares below 1% are not displayed. All results are based on reduced sample for which all relevant variables (outcome and mediator) are available.

Table 11:
The importance of mediating factors for STEM choice

	Share of rank effect mediated (%)	N
Interest in math	12.6	4,275
Math useful in future	–	4,286
Peers interested in math	–	4,177
Confident to be able to solve math problems	1.23	4,280
Good at math	11.92	4,179
Anxious about math	1.57	4,256
Perceived control at math	–	4,233
Provide effort in math	1.23	4,195

Note: This table shows the decomposition of the occupational choice effect by each related mechanism variable. We focus on the mediating role of self-belief and attitudes towards math. Shares below 1% are not displayed. All results are based on reduced sample for which all relevant variables (outcome and mediator) are available.

Table 12:
Result: Effect on human capital investment

	Vocational Education	Vocational Education: Same occupation	Vocational Education: Other occupation	Professional Education	College	Any
	(1)	(2)	(3)	(4)	(5)	(6)
C: All fields of education						
Rank Math	0.225**	0.092	0.134	0.133	-0.125	0.233
	(0.103)	(0.106)	(0.123)	(0.082)	(0.102)	(0.152)
B: Same field of education						
Rank Math	0.291***	0.091	0.200*	0.145*	-0.075	0.362**
	(0.107)	(0.106)	(0.102)	(0.075)	(0.093)	(0.167)
C: Different field of education						
Rank Math	-0.066	0.001	-0.067	-0.012	-0.051	-0.128
	(0.091)	(0.001)	(0.091)	(0.039)	(0.066)	(0.118)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	7,229	7,229	7,229	7,229	7,229	7,229
Cluster	483	483	483	483	483	483

Note: Each column reports estimates of separate regressions of years enrolled in a specific education program (see column title) between 2012-2020 on students' classroom rank in math (0-1, based on PISA-2012 scores) in the last year of compulsory school. Panel A (B) reports estimates for years enrolled in a specific education program in the same (a different) field of education as the first training occupation. Sample is restricted to students who start a vocational training program at leas one year after graduating from compulsory school. Control variables: gender, date of birth (month-times-year dummies), parental education (college education, binary), number of books at home (7 categories), migration status (4 categories), language spoken at home (official language of CH, binary), PISA-2012 test score (and squared term) in math. Robust standard errors are clustered at school-times-track level.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

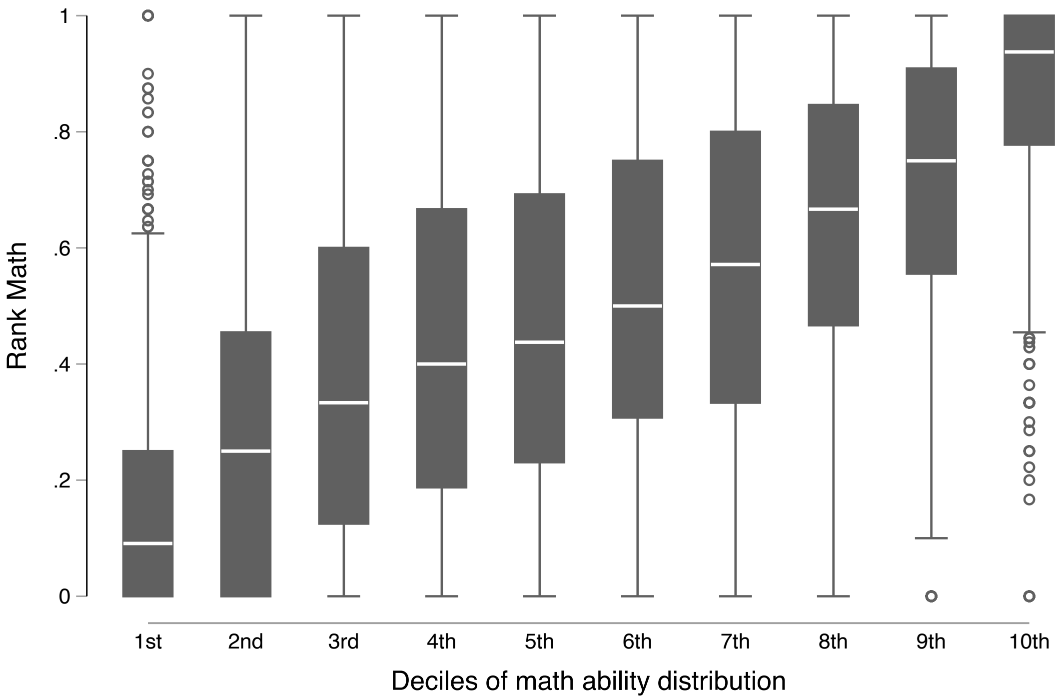
Table 13:
Dropout

	Dropout
	(1)
Rank Math	-0.022
	(0.038)
Mean value outcome	0.16
Controls	Yes
Class FE	Yes
Observation	7,229
Cluster	483

Note: The table reports estimates for the model in Equation 2, where the dependent variable is an indicator for students dropping out of the chosen educational program. We include individual level controls as specified in Equation2 and classroom fixed effects. Robust standard errors are clustered at school-times-track level.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

ONLINE APPENDIX A

Figure A1:
Global versus local rank



Note: Box-whisker plots of percentile rank measure by deciles of the global math test score distribution. Lower and upper bounds of boxes illustrate the 25th and 75th percentile (interquartile range) of the local (or conditional) percentile rank measure. The horizontal line in the box illustrates the 50th percentile of the local percentile rank measure. Whiskers represent the lowest (highest) value of the local percentile rank measure within an extended interquartile range (1.5 times the interquartile range). Dots represent single values of the local percentile rank measure outside the extended interquartile range.

Table A1:
Variation in rank

	Standard Deviation in Rank Variable										
	Full sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
No controls	0.33	0.21	0.26	0.30	0.29	0.30	0.28	0.29	0.27	0.25	0.20
Controls and classroom fixed effects	0.13	0.17	0.15	0.14	0.12	0.12	0.12	0.13	0.13	0.13	0.16

Note: The table illustrates the variation of our variable of interest across the entire sample and within ability deciles. The initial row displays the raw variation, while the subsequent row adjusts for classroom fixed effects and individual background characteristics, consistent with our preferred specification. We regress the within-class rank on individual controls and classroom fixed effects, $R_{ic} = \lambda A_{ic} + \gamma X_{ic} + \delta_c$, and then take the standard deviation of the residuals.

Table A2:
Balancing test: full sample

	Rank measure		Peer ability (mean)		Peer ability (SD)	
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.001**	0.000	-0.003*	-0.000**	0.009***	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)
Female	-0.096***	-0.010***	0.283***	0.000	-0.011	0.011
	(0.005)	(0.003)	(0.015)	(0.002)	(0.018)	(0.010)
Swiss nationality	-0.037***	0.000	0.125***	0.001	0.027	-0.014
	(0.008)	(0.005)	(0.023)	(0.004)	(0.033)	(0.015)
Language spoken at home: Swiss	-0.047***	0.003	0.161***	-0.003	0.002	-0.001
	(0.009)	(0.005)	(0.026)	(0.004)	(0.036)	(0.018)
Parental education	-0.044***	-0.004	0.134***	0.000	0.020	0.008
	(0.006)	(0.003)	(0.016)	(0.002)	(0.023)	(0.009)
More than 200 books at home	-0.032***	0.001	0.101***	-0.005*	0.063**	0.022**
	(0.007)	(0.004)	(0.018)	(0.003)	(0.028)	(0.011)
Ability controls	Yes	Yes	Yes	Yes	Yes	Yes
Class FE	No	Yes	No	Yes	No	Yes
Observation	11,684	11,684	11,684	11,684	11,480	11,480
Cluster	492	492	492	492	486	486

Note: Each cell reports estimate of a separate regression of the variable in the column header (rank, peer ability, or standard variation in peer ability) on the row variable. All specifications include controls for ability, and the even columns reports estimates with classroom fixed effects.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A3:
Balancing test: VET sample

	Rank measure		Peer ability (mean)		Peer ability (SD)	
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.001	0.001**	-0.003	-0.001	0.004	0.001
	(0.001)	(0.000)	(0.002)	(0.000)	(0.002)	(0.001)
Female	-0.090***	-0.009**	0.278***	-0.000	-0.031	-0.004
	(0.007)	(0.004)	(0.023)	(0.005)	(0.026)	(0.014)
Swiss nationality	-0.042***	0.006	0.150***	-0.000	0.065	-0.006
	(0.009)	(0.006)	(0.032)	(0.008)	(0.042)	(0.024)
Language spoken at home: Swiss	-0.057***	0.003	0.198***	-0.011	0.008	-0.013
	(0.010)	(0.006)	(0.034)	(0.010)	(0.045)	(0.023)
Parental education	-0.029***	-0.000	0.078***	0.003	-0.015	-0.003
	(0.006)	(0.004)	(0.020)	(0.005)	(0.027)	(0.013)
More than 200 books at home	-0.007	0.000	-0.020	-0.016**	0.043	0.011
	(0.009)	(0.006)	(0.028)	(0.007)	(0.038)	(0.022)
Ability controls	Yes	Yes	Yes	Yes	Yes	Yes
Class FE	No	Yes	No	Yes	No	Yes
Observation	7,229	7,229	7,066	7,066	6,752	6,752
Cluster	483	483	461	461	437	437

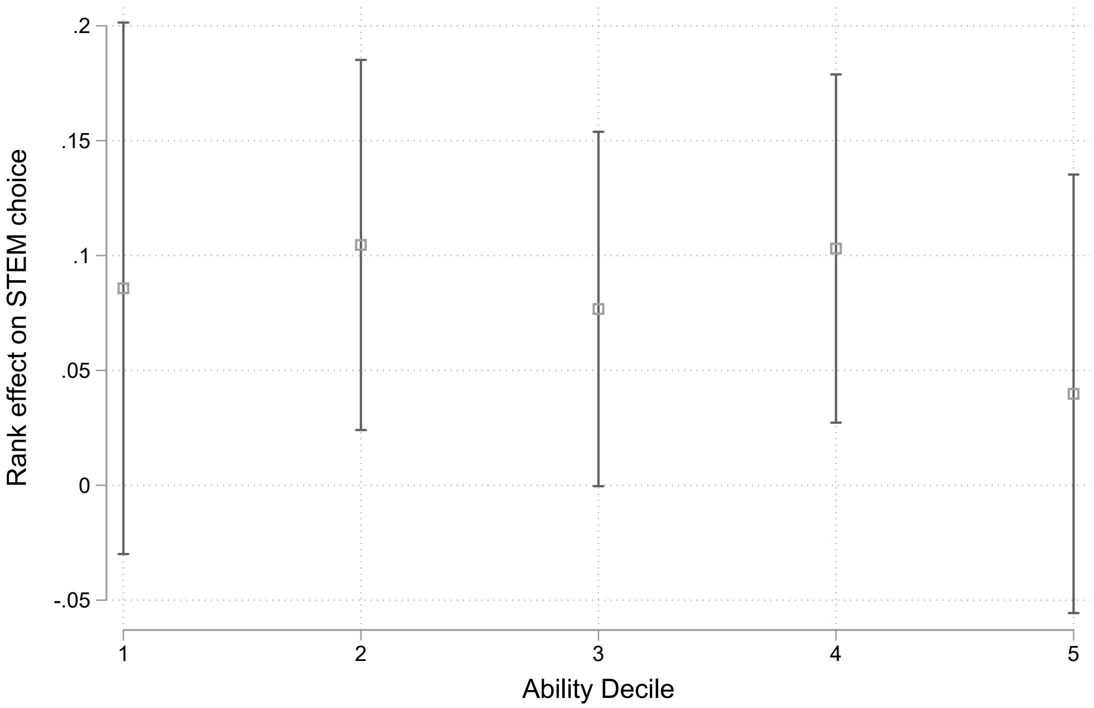
Note: Each cell reports estimate of a separate regression of the variable in the column header (rank, peer ability, or standard variation in peer ability) on the row variable. All specifications include controls for ability, and the even columns reports estimates with classroom fixed effects.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A4:
Main result: Normalized rank

	(1)	(2)	(3)	(4)
Rank Math	0.030**			0.029**
	(0.013)			(0.014)
Rank Reading		0.005		-0.001
		(0.013)		(0.014)
Rank Science			0.007	-0.008
			(0.013)	(0.015)
Controls	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes
Observation	6,580	6,580	6,580	6,580
Cluster	480	480	480	480

Note: The table reports estimates of model 2, where rank enters the equation with a set of indicators for each tercile of the rank distributions The second tercile is the reference category. We include individual level controls as specified in 2 and classroom fixed effects. Robust standard errors are clustered at school-times-track level.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Figure A2:
Heterogeneity: Effects of ordinal rank by ability quintile



Note: Each dot illustrates the coefficient estimate of classroom rank in math of separate regressions by ability quintiles. Classroom fixed effects, control variables, and PISA-2012 math score (and squared term) included. Vertical lines indicate 90% confidence intervals. Robust standard errors are clustered at school-times-track level.

Table A5:
Attitudes variables details

- Interest in math (these are all the ST29 questions -if they have the same name in the dataset you have)
  - I enjoy reading about mathematics
  - I look forward to my mathematics lessons
  - I do mathematics because I enjoy it
  - I am interested in the things I learn in mathematics
- Math useful in future
  - Making an effort in mathematics is worth it because it will help me in the work that I want to do later on
  - Learning mathematics is worthwhile for me because it will improve my career <prospects, chances>
  - Mathematics is an important subject for me because I need it for what I want to study later on
  - I will learn many things in mathematics that will help me get a job
- Peers interested in math
  - Most of my friends do well in mathematics
  - Most of my friends work hard at mathematics
  - My friends enjoy taking mathematics tests
  - My parents believe it's important for me to study mathematics
  - My parents believe that mathematics is important for my career
  - My parents like mathematics
- Confident to be able to solve math problems
  - Using a <train timetable> to work out how long it would take to get from one place to another
  - Calculating how much cheaper a TV would be after a 30% discount
  - Calculating how many square metres of tiles you need to cover a floor
  - Understanding graphs presented in newspapers
  - Solving an equation like $3x + 5 = 17$
  - Finding the actual distance between two places on a map with a $1 : 10000$ scale
  - Solving an equation like $2(x + 3) = (x + 3)(x - 3)$
  - Calculating the petrol consumption rate of a car
- Good at math
  - I am just not good at mathematics
  - I get good <grades> in mathematics
  - I learn mathematics quickly
  - I have always believed that mathematics is one of my best subjects
  - In my mathematics class, I understand even the most difficult work
- Anxious about math
  - I often worry that it will be difficult for me in mathematics classes
  - I get very tense when I have to do mathematics homework
  - I get very nervous doing mathematics problems
  - I feel helpless when doing a mathematics problem
  - I worry that I will get poor <grades> in mathematics
- Perceived control at math
  - If I put in enough effort I can succeed in mathematics
  - Whether or not I do well in mathematics is completely up to me
  - Family demands or other problems prevent me from putting a lot of time into my mathematics work
  - If I had different teachers, I would try harder in mathematics
  - If I wanted to, I could do well in mathematics
  - I do badly in mathematics whether or not I study for my exams
- Provide effort in math
  - I finish my homework in time for mathematics class
  - I work hard on my mathematics homework
  - I am prepared for my mathematics exams
  - I study hard for mathematics quizzes
  - I keep studying until I understand mathematics material
  - I pay attention in mathematics class
  - I listen in mathematics class
  - I avoid distractions when I am studying mathematics
  - I keep my mathematics work well organised

Note: Items of the Main Survey PISA-2012, that were used to measure the corresponding attitudes towards mathematics. The grouping is in line with PISA-2012 Technical report. The response categories range from “Strongly agree” to “Strongly disagree”.

Table A6:
Robust: Effect on STEM intensity (missings coded as 0)

	(1)	(2)	(3)	(4)
Rank Math	0.085**			0.076*
	(0.037)			(0.040)
Rank Reading		0.016		0.001
		(0.037)		(0.039)
Rank Science			0.025	-0.018
			(0.037)	(0.042)
Controls	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes
Observation	7,229	7,229	7,229	7,229
Cluster	483	483	483	483

Note: Each column reports estimates of separate regressions of a variable indicating the STEM intensity of the first training occupation (in percent, Panel A) or a binary variable indicating if the STEM intensity of a students' first training occupation lies in the 4th quarter of the STEM intensity distribution of all training occupations (Panel B) on students classroom rank in math and/or science and/or reading (0-1, based on PISA-2012 scores) in the last year of compulsory school. Sample is restricted to students who start a vocational training program within one year after graduating from compulsory school. Control variables: gender, date of birth (month-times-year dummies), parental education (college education, binary), number of books at home (7 categories), migration status (4 categories), language spoken at home (official language of CH, binary), PISA-2012 test score (and squared term) in math (columns 1, 4), reading (columns 2, 4), science (columns 3, 4). Robust standard errors are clustered at school-times-track level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A7:
Robust: Effect on STEM intensity (missing coded as 1)

	(1)	(2)	(3)	(4)
Rank Math	0.111**			0.115**
	(0.043)			(0.045)
Rank Reading		-0.009		-0.027
		(0.041)		(0.042)
Rank Science			0.017	-0.034
			(0.044)	(0.049)
Controls	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes
Observation	7,229	7,229	7,229	7,229
Cluster	483	483	483	483

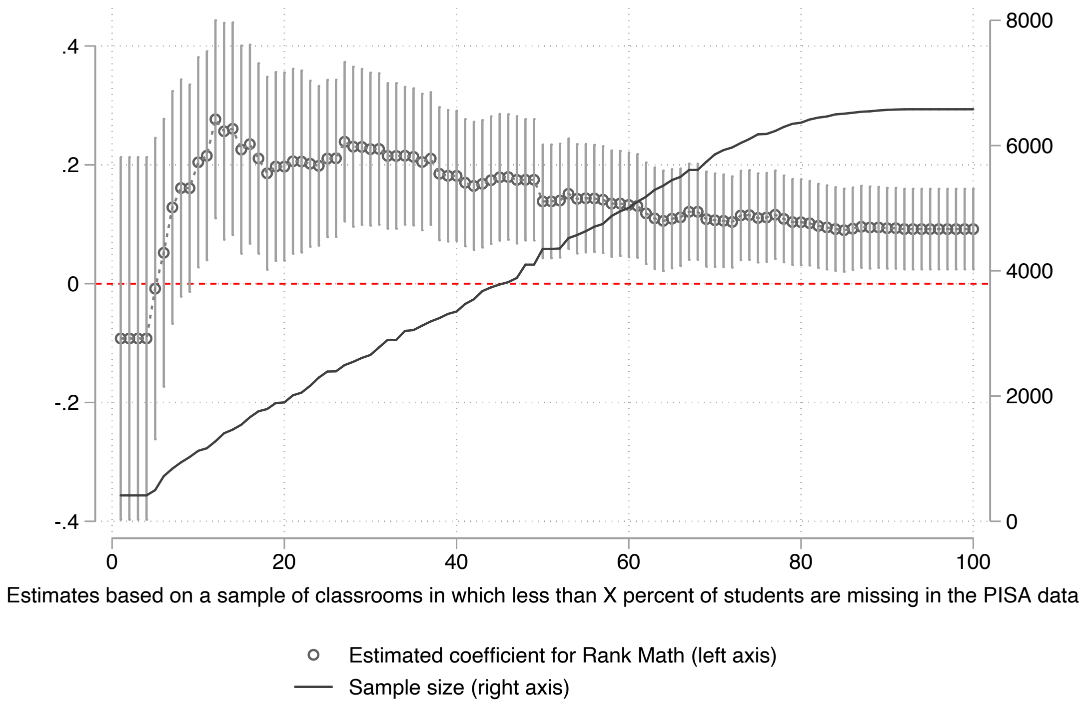
Note: Each column reports estimates of separate regressions of a variable indicating the STEM intensity of the first training occupation (in percent, Panel A) or a binary variable indicating if the STEM intensity of a students' first training occupation lies in the 4th quarter of the STEM intensity distribution of all training occupations (Panel B) on students classroom rank in math and/or science and/or reading (0-1, based on PISA-2012 scores) in the last year of compulsory school. Sample is restricted to students who start a vocational training program within one year after graduating from compulsory school. Control variables: gender, date of birth (month-times-year dummies), parental education (college education, binary), number of books at home (7 categories), migration status (4 categories), language spoken at home (official language of CH, binary), PISA-2012 test score (and squared term) in math (columns 1, 4), reading (columns 2, 4), science (columns 3, 4). Robust standard errors are clustered at school-times-track level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A8:
Robust: Different definitions of STEM-intensive occupations

	(1)	(2)	(3)	(4)
A: STEM-intensity of occupation (continous)				
Rank Math	2.144**			1.660
	(1.059)			(1.172)
Rank Reading		0.834		0.506
		(0.942)		(0.984)
Rank Science			0.987	-0.166
			(1.021)	(1.156)
B: STEM occupation (binary, 90th percentile)				
Rank Math	0.064**			0.060*
	(0.032)			(0.034)
Rank Reading		0.002		-0.017
		(0.029)		(0.031)
Rank Science			0.031	0.007
			(0.034)	(0.037)
C: STEM occupation (binary, 50th percentile)				
Rank Math	0.034			0.025
	(0.043)			(0.047)
Rank Reading		0.024		0.032
		(0.039)		(0.042)
Rank Science			-0.005	-0.035
			(0.043)	(0.049)
Controls	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes
Observation	6,580	6,580	6,580	6,580
Cluster	480	480	480	480

Note: Each column estimates the model in Equation 2, with math intensity of an occupation (the dependent variable) measured with a continuous variable (Panel A), with an indicator variable for occupations falling within the 90th percentile of the STEM intensity distribution (Panel B), or within the 50th percentile of the STEM intensity distribution (Panel C), respectively. Robust standard errors are clustered at school-times-track level.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Figure A3:
Robust: Students missing from classroom



Note: Each dot reports estimates of our baseline effect of students' classroom rank in math on occupational choice (Table 4, column 1). Estimates are based on subsamples of classrooms in which less than a varying number of students (measured in percent on the x-axis) students are missing in the PISA-2012 data. The bold line indicates the number of observations included for each regression. Standard errors are clustered at school-times-track level. Vertical lines indicate 90 %-confidence interval.

Table A9:
Robust: Heterogeneity by school ability distribution

	(1)	(2)	(3)
Rank Math	0.094**	0.071*	0.073*
	(0.041)	(0.043)	(0.043)
Ability interacted with:			
School Mean Ability	Yes	No	Yes
School Variance Ability	No	Yes	Yes
Controls	Yes	Yes	Yes
Class FE	Yes	Yes	Yes
Observation	6,580	6,567	6,567
Cluster	480	467	467

Note: Each column controls for either average school ability, either variance of school ability, either both, interacted with the rank measure. We include individual level controls as specified in Equation 2 and classroom fixed effects. Robust standard errors are clustered at school-times-track level.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A10:
Robust: Non-linearity in ability

	(1)	(2)	(3)	(4)	(5)
Rank Math	0.092**	0.080*	0.080*	0.085**	0.084**
	(0.041)	(0.042)	(0.042)	(0.039)	(0.041)
Math ability control					
2nd-degree polynomial	Yes	No	No	No	No
3rd-degree polynomial	No	Yes	No	No	No
4th-degree polynomial	No	No	Yes	No	No
Binary variables (5 quantiles)	No	No	No	Yes	No
Binary variables (10 quantiles)	No	No	No	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes	Yes
Observation	6,580	6,580	6,580	6,580	6,580
Cluster	480	480	480	480	480

Note: Each column estimates the model in Equation 2, including either different absolute math ability binary variables polynomials (columns (1) to (3)), or different quantiles of the absolute math ability distribution (columns (4) and (5). We include individual level controls as specified in Equation2 and classroom fixed effects. Robust standard errors are clustered at school-times-track level.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.