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# Classroom rank in math, occupational choices and labor market outcomes[*]

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**Abstract**

We study the impact of a student's classroom rank in math on subsequent educational and occupational choices, as well as labor market outcomes. Using the Swiss PISA-2012 student achievement data linked to administrative student register data and income information from tax records, we exploit differences in math achievement distributions across classes to estimate the effect of students' ordinal rank in the classroom. We find that students with a higher classroom rank in math are more likely to select into occupations that require a higher share of math and science skills. We then show this has lasting effects on earnings in the labor market several years after completing compulsory school and is associated with a higher willingness to invest in occupation specific further education. We use detailed subject specific survey information to show that students rank in math is associated with an increase in perceived ability in math and with increasing willingness to provide effort in math. The latter channel may offset potential consequences for occupation mismatch if occupational choices are based on perceived rather than actual ability, as we do not find that rank based decisions lead to increases in occupational changes.

**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 for 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 limited attention in the context of occupational choices, is students' ordinal rank in the classroom.

Students face considerable uncertainty when making educational and occupational choices. This uncertainty stems in part from the fact that objective information on own ability is often limited. Therefore, students may rely on the comparison to their peers to gauge their ability. Hence, a student's ability rank – meant as her ordinal position in the ability distribution her group of peers – can be an important factor, apart from actual ability, to influence educational and occupational choices. The same argument applies to subject specific skills. Between two otherwise identical students, the one with the higher relative (perceived) ability in a specific subject can have higher incentives for selecting, early in her career, occupations that require skills in that particular domain.

In this paper, we explore how a student's rank in specific subjects during compulsory schooling impacts their later occupational choices, earnings, and investments in further education. 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 math and its association with the likelihood of pursuing careers in STEM fields.

We utilize a unique data set that combines the Swiss PISA-2012 student assessment test with longitudinal administrative records, along with new data on the skill requirements for various occupations and income information from tax records. Our extensive set of data enables us

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

to establish connections between students' classroom rank in lower-secondary school in various subjects (assessed through comparable PISA test scores) and their subsequent occupational choices, their outcomes in the labor market, and their investments in education and skills 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 (Denning et al., 2021). We employ regression models that account for classroom-specific factors and include comprehensive controls for students' individual math abilities. This allows us to examine how a student's math rank in the classroom influences their occupational choices and other long-term outcomes. Furthermore, using specific questions about math in the PISA-2012 background questionnaires, we investigate the underlying mechanisms. In particular, this set of questions allows us to explore whether the observed rank effects stem from students' self-perception of their math abilities and/or the level of effort they invest in the subject. Finally, we investigate the potential negative consequences of occupational choices based on perceived rather than actual ability for the skill match between students and occupations. The match of skills between workers and their respective occupations is a critical factor affecting firm productivity, individual wage growth, and career transitions (Patterson et al., 2016; Fredriksson et al., 2018; Baley et al., 2022). In our context, decisions based on perceived rather than actual ability may lead to a misalignment between students' skills and the skill requirements of their chosen occupations.

We document three sets of results. 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 to choose a training occupation that is positioned in the 4th decile of the STEM skill distribution (or a 13% increase relative to the sample mean).

Furthermore, we show that parental education plays a crucial role in the significance of rank effects. Students with highly educated parents are less likely to base their choices on classroom rank, in contrast to students whose parents did not pursue tertiary education. Building on the findings of a recent study by Dizon-Ross (2019), 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, in line with previous research emphasizing the positive link between the math or STEM intensity of occupations and earnings (Joensen and Nielsen, 2009). 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 CHF (equivalent to a 9.4% rise relative to the sample mean).

Finally, we also show that students with higher ranks are more likely to acquire further human capital beyond the initial training program and more likely to acquire an additional education that facilitates self-employment. Moreover, following Fouarge and Heß (2023), who showed that students embarking on a program not aligned with their previously expressed preferences are more likely to discontinue their studies, we analyse the link between the classroom rank in math and dropout. Our analysis does not reveal any evidence that occupational choices based on rank lead to a greater likelihood of dropping out from the initial chosen occupation or switching to an occupation in a different educational field.

In line with existing research suggesting that rank effects may influence students' beliefs and behaviors (Elsner and Isphording, 2017; Kiessling and Norris, 2023), our analysis uncovers a robust connection between classroom math rank and various indicators of students' attitudes toward math, as well as their level of effort in the subject. Specifically, students ranking higher within their classroom distribution are more likely to exhibit greater confidence in their math abilities and a heightened willingness to put effort into studying math. The latter may help to offset potentially negative consequences of rank based occupational choices.

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, 2022), 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 and occupational decisions of students in community colleges and vocational education programs, despite their significant implications for labor market outcomes (Acton, 2021; Wolter and Ryan, 2011). We focus on training program choices immediately after compulsory schooling. Understanding these choices is crucial, as graduates of STEM vocational education programs experience significant earnings gains compared to other vocational programs with limited benefits beyond a high-school diploma (Acton, 2021). Additionally, students in vocational education programs may face greater challenges in adapting to changing labor market demands (Dauth et al., 2021). In sum, our study makes a unique contribution by examining the influence of naturally occurring peer effects in the school environment on occupational choices. Our findings emphasize the role of perceived ability, beyond actual ability. Furthermore, we uncover the long-term impact of classroom ranks on labor market outcomes using administrative data, including earnings and individuals' willingness to pursue further education, several years after completing their occupational training program.

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. This effect has been shown to influence educational outcomes (Elsner and Isphording, 2017; Murphy and Weinhardt, 2020; Elsner et al., 2021; Delaney and Devereux, 2021), labor market earnings (Denning et al., 2021), bullying (Comi et al., 2021), skill development (Pagani et al., 2021), and mental health (Kiessling and Norris, 2023).[2] While our study shares a similar empirical strategy with some previous works on rank effects, our focus differs significantly. We examine the influence of the classroom rank in math on occupational choices. Occupational choices in vocational education training programs are directly linked to future careers, making them highly consequential. Moreover, we utilize the comprehensive survey data from the PISA tests to demonstrate the importance of effort provision as a mediating channel. This finding aligns with the observation that students continue to

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

invest effort even after completing their vocational programs.

Third, we contribute to the growing body of literature on horizontal mismatch (Robst, 2007; Fredriksson et al., 2018; Carranza et al., 2022). While many studies explore how skill mismatch impacts firm productivity and workers' careers (Guvenen et al., 2020; Baley et al., 2022; Patterson et al., 2016; Neffke et al., 2022), there is limited evidence regarding the causes of occupational mismatch. Guvenen et al. (2020) uses a model to demonstrate that skill mismatch can arise due to imperfect information and Bayesian learning. Building upon this research, we investigate whether individuals selecting jobs based on their classroom rank rather than their actual abilities, lead to lasting consequences such as dropout and occupational switches.

The rest of the paper is organized as follows. The next section provides a short explanation of the Swiss educational system. Section 3 presents information about the data used and the variables of interest, while Section 4 describes the empirical strategy in more detail and discusses our identification strategy. Sections 5 and 6 present the main results on education and labor market outcomes. Section 7 concludes.

## 2 Education system in Switzerland

The compulsory education system in Switzerland consists of two years of kindergarten, primary school (six years, grades 1-6), and lower secondary school (three years, grades 7-9). Around 95% of students of compulsory-school-age attend public schools, free of charge and considered to be of high quality (Nikolai, 2019). School choice is limited by a legal obligation to attend schools in the area where one lives (Diem and Wolter, 2013).

Starting in lower secondary school, students are tracked in accordance with their academic ability. Roughly one third of students of each cohort are assigned to a track with basic requirements (low-track) and the other two third attend a track with extended requirements. In the last year of compulsory school (9th grade), students can follow mainly two different upper secondary education paths.[3] Students who enroll in a fully school-based general education track (baccalaureate schools) and aim for academic degrees at institutions of higher education (e.g., universities). 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

[3]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).

occupations that span across various sectors and industries. Vocational programs teach students occupation-specific practical and theoretical skills, preparing them for non-academic careers in the labor market. Programs consist of a combination of school and firm training, with students being trained partly at training firms through on-the-job apprenticeships a (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 the potential apprentices from the pool of applicants after a selection process. After finishing the training for the chosen occupation, apprentices 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 of a training occupation at the secondary level is highly significant for career opportunities and 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.[4]

In our analysis, we employ the extended version of the Swiss section of the PISA-2012 wave. While the regular sample comprises around 5 000 9th graders, the extended version in Switzerland of the PISA 2012-wave, incorporating additional representative regional samples, consists of roughly 12 000 students, whose math, science, and reading skills were assessed via pencil-and-paper tests. Besides information on math, science, and reading ability measures, PISA collects a

[4]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, individual schools are randomly sampled, and secondly, a randomly selected set of students from each school participate. For a more detailed description on the design an structure of PISA tests see also for example Griselda (2024).

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 data is matched to student annual registry data from the universe of students in Switzerland covered by the LABB data (Längsschnittanalysen im Bildungsbereich). Individual identifiers included in the dataset allow us to track students across several years, their transition into upper-secondary education and beyond and to follow their educational pathways from 2012 to 2020. The LABB dataset entails yearly details on students' ongoing educational status, encompassing factors such as the type and location of educational institutions, school tracks, and grades, along with a range of student background characteristics, including age, gender, first language, and migration status. It also contains class identifiers, which we use to define a students peer group.[5]

Second, we link information on the cognitive skill requirements of the specific training occupation (math, natural science, language, foreign language). This information is used 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.[6] These skill requirements, 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 the labor market until the year 2020 and match 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 with two restriction. First, we include only students for whom we have at least one

[5]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.

[6]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 successfully complete the VET program.

other student observation in the same classroom in the PISA data. 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 test score result.

Unsurprisingly, we do not find differences among school characteristics between low- and high-ranked students in the classroom. Most students are located in the German and French language regions of Switzerland. Roughly two-thirds of the students enroll into a vocational program after the end of compulsory schooling, again an information 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 strongly 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. As omission would bias our rank effect estimates, we follow the approach of Elsner and Isphording (2017) and include these variables in our empirical analysis as control variables. For more details on the identification strategy see Section 4.

### 3.3 Outcome variables

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

The occupational choices of students selecting into vocational education programs is assessed using information on 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 requirement 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 empirical analysis, we use our STEM intensity measure both as a continuous variable and a binary variable indicating training occupations with a high STEM intensity (i.e., fourth quarter of the stem intensity distribution).

Information on income are 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 into 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 into the vocational education track have higher earnings in the years after compulsory school compared to students selecting the general education track since they enter the labor market earlier.

Finally, we use our detailed student register data to obtain information on students human capital investments and their likelihood of dropout after compulsory schooling. Specifically, we calculate the number of years a student is enrolled at a particular Swiss educational institution. Moreover, for students who started a vocational education program, we are able to 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 percentage of students who start a specific education program and the average years enrolled in a corresponding program *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 (see professional education and college).

### 3.4 Relative rank

In our empirical analysis, we use students' percentile rank in math in the classroom to measure students' math ability rank. We measure the math ability by relying on students' performance in the PISA test. To compute the percentile rank in math $R_{ic}$ of student $i$ in classroom $c$, we first determine student $i$'s absolute rank in math in the classroom, $n_{ic}$, by sorting students in accordance with 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 in 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 exhibit 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 or labor market outcome in a given year of student $i$ in 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 own 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 $\epsilon_{ic}$ represents an error term. Additionally, we add a set of classroom fixed-effects, $\delta_c$.

Our coefficient of interest is $\beta$, measuring the relationship between the outcome of interest and the ordinal classroom rank in math. In order 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 $\epsilon_{ic}$ is uncorrelated with a student's ordinal math rank given their own 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 own 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 actual grades, we do observe evidence supporting the idea that students are aware about 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 own absolute ability, a link that indicates 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 teachers-assigned grades.[7]

### 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

[7] A disadvantage of the PISA-based rank measure is that we do not observe the PISA scores for every student in each class. The validity of the rank measure therefore relies on the random sampling of students in the PISA 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.

heterogeneity of a classroom, we use classroom fixed effects following Murphy and Weinhardt (2020), Denning et al. (2021) 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.[8]

#### 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 true, 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 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.[9]

## 5 Ordinal rank and occupational choices

We begin our analysis by examining the impact of students' ordinal rank in math on the STEM intensity of their chosen occupation. Table 4 presents our findings. The dependent variable

[8] For a more detailed discussion on the challenges to identify rank effects see Denning et al. (2021).

[9] 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.

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, the absolute ability level of each student, determined by utilizing a second-order polynomial function based on their corresponding PISA score, and standard errors clustered by school-by-track level.[10]

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 student 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 13% increase relative to the sample mean (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. Furthermore, our results regarding math rank remain statistically significant even after controlling for rank measures in science and reading (Column 4). This indicates that the impact of classroom rank in math on occupational choices is distinctive and not merely a reflection of general classroom rank effects.

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

[10]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.

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.[11]

### 5.1 Heterogeneity

In our main specification, we used a linear estimation procedure. While some researchers 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., 2021). To explore the potential presence of nonlinear effects, 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.

Extensive research has uncovered distinct behavioral patterns between boys and girls, highlighting several notable differences. Some of these findings, relevant to our study, include the observation 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 the significant under-representation of female students in STEM occupations (e.g. Cimpian et al. (2020); Goulas et al. (2022)). This pat-

[11] 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.

tern is similar in Switzerland.[12] To discern gender-specific effects more precisely, we introduce interaction terms between math rankings and indicators for male gender in our analysis. The results are presented in Panel A of Table 7. However, our analysis does not reveal any significant evidence for a differential response to classroom rank in math between boys and girls.

Next, we investigate whether the effect of math rank differs among native students and students with a migration background. With regard to migration status, the economics literature on peer effects has so far often focuses on the effect of the share of minority peers on the outcomes of the general population (e.g. Ballatore et al. (2018); Bossavie (2020)). Since the share of students with migration background is steadily increasing and students with migration background a largely underrepresented in VET, we pay particular attention how the classroom ranks affects outcomes of both, native students and students with migration status. In Panel B of Table 7 we show that there is not statistically significant difference among both groups.

Finally, 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 decisions (Figlio et al., 2019). One way parents may impact their children's educational choices is by forming beliefs about their abilities. 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). 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 result. 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 explain students' outcomes due to classroom rank (Murphy and Weinhardt, 2020; Elsner and Isphording, 2017; Kiessling and Norris, 2023). To assess the relationship between classroom rank in math and students' beliefs and behavior, we leverage detailed subject-specific information from the PISA-2012 questionnaire.

[12] Apart from the distribution of the STEM intensity measure, 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 into occupations with lower STEM intensity.

Specifically, we examine students' responses to eight 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.

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 Column 5 and Column 7, we demonstrate 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 the subject of math, as well as students' willingness to put effort into the subject (as shown in Column 1 and Column 8). This positive association between subject-specific ranks and effort indicates that adolescents respond to ability ranks in terms of their school and subject-specific behaviour, and these effects seem to operate through students' beliefs. This result is a novel contribution to the literature and may also help explain findings in related studies (Elsner et al., 2021). 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 A5 and Table A6, 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 A5) or a 1 math intensity measure (Table A6). 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 A7 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 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 those within the 90th percentile. However, the effect is substantially smaller when using the broader definition of a STEM occupation.

Moreover, we address concerns related to the specific sampling procedure used in the PISA 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 of a classroom in some cases, while in other cases, it relies on a random sample of students. In Figure A2, 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 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 the 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., 2021). 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 showed in Section

5. We start our investigation by examining the association between classroom rank in math and earnings in the years following compulsory education (Section 6.1). Following that, we turn our attention to investments in human capital as another crucial determinant of labor market success in Section 6.2. 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 $\beta$ 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 sub-sample of students who choose a vocational education training program. For completeness, Figure 3c displays results for the non-VET sub-sample, while Figure 3b presents the results on the entire sample.

In Figure 3a, we observe a positive and slightly increasing impact of our rank measure on yearly income from 2015 onward. For the period spanning 2016-2020, the estimated coefficient falls within a range of CHF 1,748 to CHF 3,221. For perspective, in 2020, the highest estimate year, 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.[13]

Figure 3b, 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) but opting for general educational programs invest in a minimum of two additional school years and in several university years. As a result, the vast majority of this group does not enter the labor market before 2020. Figure 3c illustrates the resulting lack of association between our treatment and earnings for the non-VET students sub-sample.

[13]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.

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 has an effect on students' subsequent earnings. In Panel B, our estimate suggests that ranking in 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.

Our finding that the classroom rank in math is associated with higher earnings is in line with previous findings by Denning et al. (2021) for the U.S. Our results in Section 5 suggest that STEM choices, due to its high returns, may be an important mechanism behind this effect. However, an important question given our presented results is whether subject-specific classroom ranks also matters apart from the occupational choice.[14]

### 6.2 Investments in human capital

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)). To investigate whether classroom rank in math influences the propensity to pursue post-compulsory education, we examine whether students with higher ranks allocate more time towards increasing their human capital beyond their initial vocational education and training (VET) program. Table 10 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 10 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

[14] In results not shown in this paper we looked at the probability to be 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.

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 occupational areas (Panel B). 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 established 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. A valid concern 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) found that well-informed college choices significantly impact persistence and graduation rates. To explore this issue, we investigates whether classroom rank in math has negative consequences for persistence rates within the chosen occupation. This finding would suggest that students with higher math rank might overestimate their ability and opt for occupations for which they are not ideally suited.

To assess this hypothesis, we employ two measures of occupational persistence. First, we examine the time spent within occupations in diverse educational fields as opposed to 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 10, 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 A11, 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, our analysis does not provide compelling evidence that occupational choices influenced by perceived ability, rather than actual ability, result in dropout from the initial occupational choice. However, this finding does not imply that the observed matches between students and occupations are necessarily efficient. In fact, it could be that the impact on the willingness to provide subject-specific effort, 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. One the one hand relative rankings are an inherent feature of social environments, on the other hand math ability has been shown to be of large 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-focused occupation. To shed light on the mechanisms behind this effect, we show that the classroom rank in math is positively associated with perceived math ability and the willingness to put effort in studying math. This finding is in line 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 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, hence having those students relying more intensely on the rank based information.

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 in terms of income several years after completing compulsory schooling. Finally, we provide evidence that a higher classroom rank in math translates into higher investments in educational programs after compulsory education. On a different margin, we examine whether rank-based decisions contribute to horizontal mismatches which result in dropout from training occupations or occupational switches. Our findings indicate that while classroom rank in math influences students' occupational choices, this influence does not result in heightened dropout rates from training occupations. This could be attributed to the increased effort exerted by students.

Our study underscores the crucial role of the classroom environment, in particular students' math rank, in shaping not only short-term outcomes, such as occupational choices, but also long-term educational and labor market outcomes, such as their income levels. We also suggest that changes in students' behavior and beliefs serve as potential mechanisms for these observed effects. These findings highlight the importance of considering social dynamics within educational settings when evaluating students' career decisions. Our study also encourages further research in at least two ways. First, it stresses the importance of research that seeks to understand how to overcome rank based occupational choices. Second, it points towards the importance of understanding the consequences of relative feedback mechanisms on educational investment decisions.

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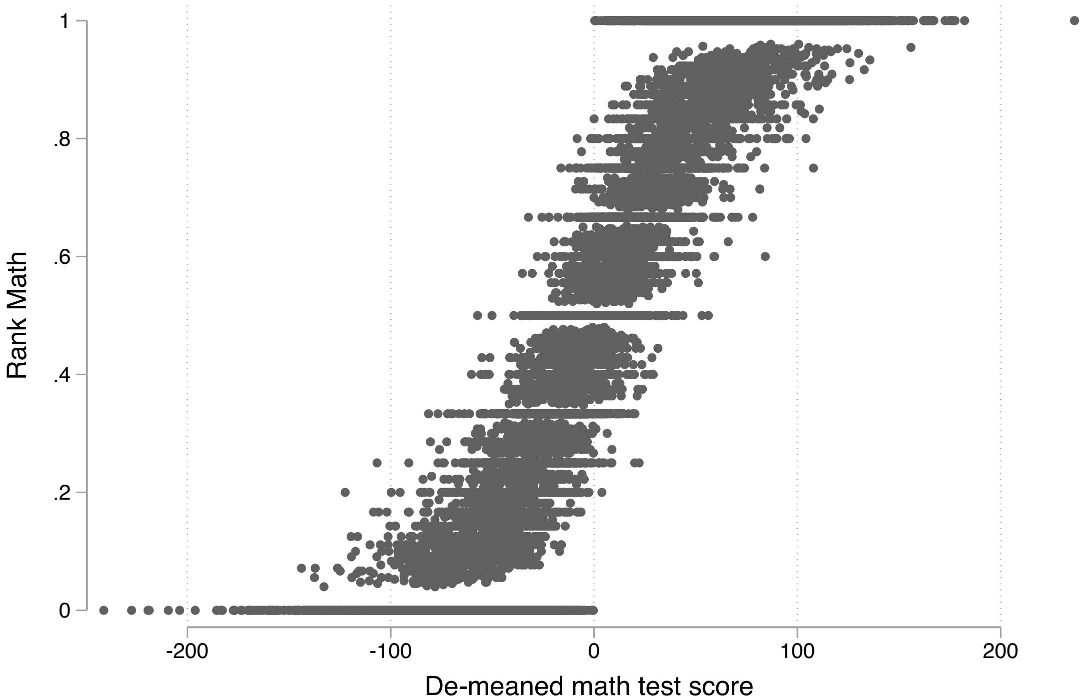
**TABLES AND FIGURES**

**Figure 1:**
**Distribution of rank measure across classrooms**



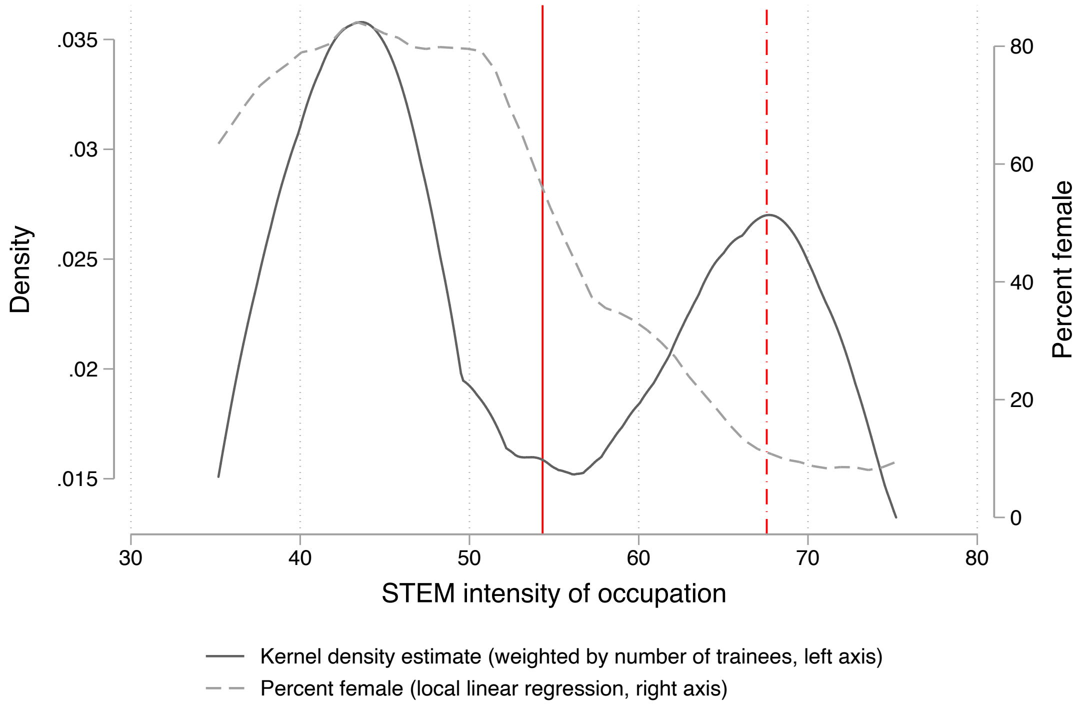

*Note:* Scatter plot of percentile rank measure in math (on the Y-axis) and de-meaned classroom-level math test scores in math (on the X-axis).

**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 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 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 |
|---|---|---|---|
| *Income (CHF)* | | | |
| 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 |
| *Educational choices* | | | |
| General education | | | |
| Started (%) | 16.6 | 100.0 | 14.9 |
| Years enrolled | 0.22 | 3.62 | 0.34 |
| Vocational education | | | |
| Started (%) | 100.0 | 13.3 | 71.4 |
| Years enrolled | 3.69 | 0.38 | 2.23 |
| Professional education | | | |
| Started (%) | 16.1 | 3.6 | 6.7 |
| Years enrolled | 0.31 | 0.08 | 0.11 |
| College | | | |
| Started (%) | 18.9 | 83.0 | 10.0 |
| Years enrolled | 0.52 | 3.26 | 0.25 |
| *Observations* | 7,229 | 3,682 | 773 |

*Note:* Mean values of students' income and educational choices after compulsory school by track-choice. *Years enrolled* in an education program refers to the mean value of the corresponding subsample (VE students, GE students, others). To obtain the mean value for the subsample of students who start a given education program, divide *Years enrolled* by the share of students who started a given education program.

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

| | All fields | Same education field | Other education field |
|---|---|---|---|
| Vocational education | | | |
| Started (%) | 100.0 | 100.0 | 10.0 |
| Years enrolled | 3.69 | 3.41 | 0.27 |
| Same occupation | | | |
| Started (%) | 100.0 | 100.0 | 0.0 |
| Years enrolled | 2.89 | 2.89 | 0.00 |
| Different occupation | | | |
| Started (%) | 35.2 | 26.6 | 10.0 |
| Years enrolled | 0.80 | 0.53 | 0.27 |
| Professional education | | | |
| Started (%) | 16.1 | 12.4 | 3.8 |
| Years enrolled | 0.31 | 0.25 | 0.06 |
| College | | | |
| Started (%) | 18.9 | 12.1 | 7.6 |
| 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 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 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:**
**Robust: 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 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 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 gender* | |
| Rank Math | 0.088* |
| | (0.046) |
| Rank Math x Female | 0.007 |
| | (0.035) |
| *B: By migration background* | |
| Rank Math | 0.106** |
| | (0.042) |
| Rank Math x Migration background | -0.061 |
| | (0.042) |
| *C: By parental education* | |
| Rank Math | 0.133*** |
| | (0.044) |
| Rank Math x College educated parents | -0.086** |
| | (0.034) |
| Controls | Yes |
| Class FE | Yes |
| Observation | 6,580 |
| Cluster | 480 |

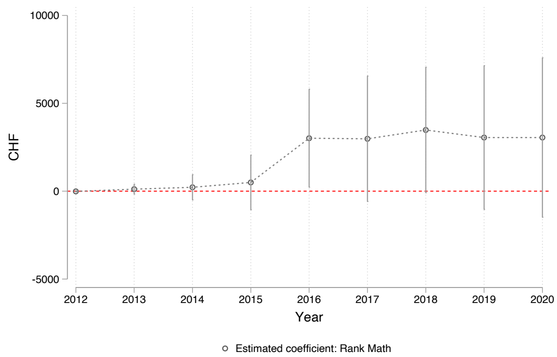
*Note:* "Migration background" in Panel B is an indicator variable for non-native students. "College educated parents" is an indicator variable for students whose parents have achieved at least college education. We include individual level controls as specified in Equation 2 and classroom fixed effects. 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**

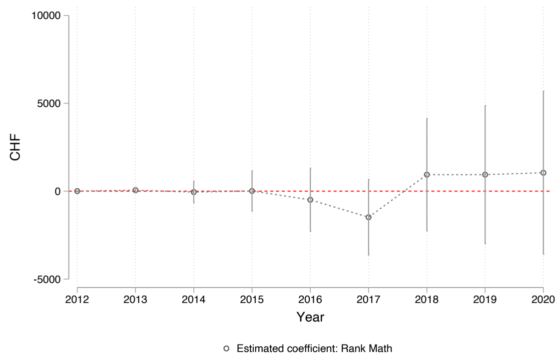
| | Interest in math | Math useful in future | Peers interested in math | Confident to be able to solve math problems | Good at math | Anxious about math | Perceived control at math | Provide effort in math |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *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 math test score (and squared term). Panel B and D include additional control variables for students' PISA reading test score (and squared term). Panel C and D include additional control variables for students' PISA science test score (and squared term). Robust standard errors clustered at school-times-track-level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

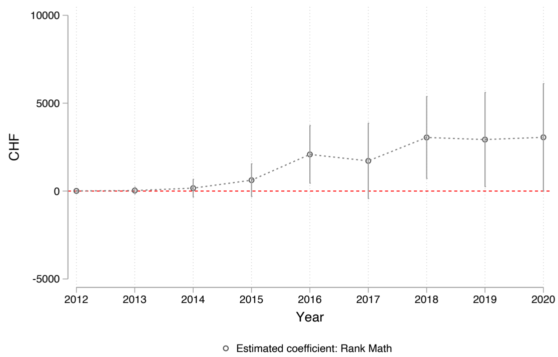
**Figure 3:**
**Results: Effect on income**




**(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 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 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.

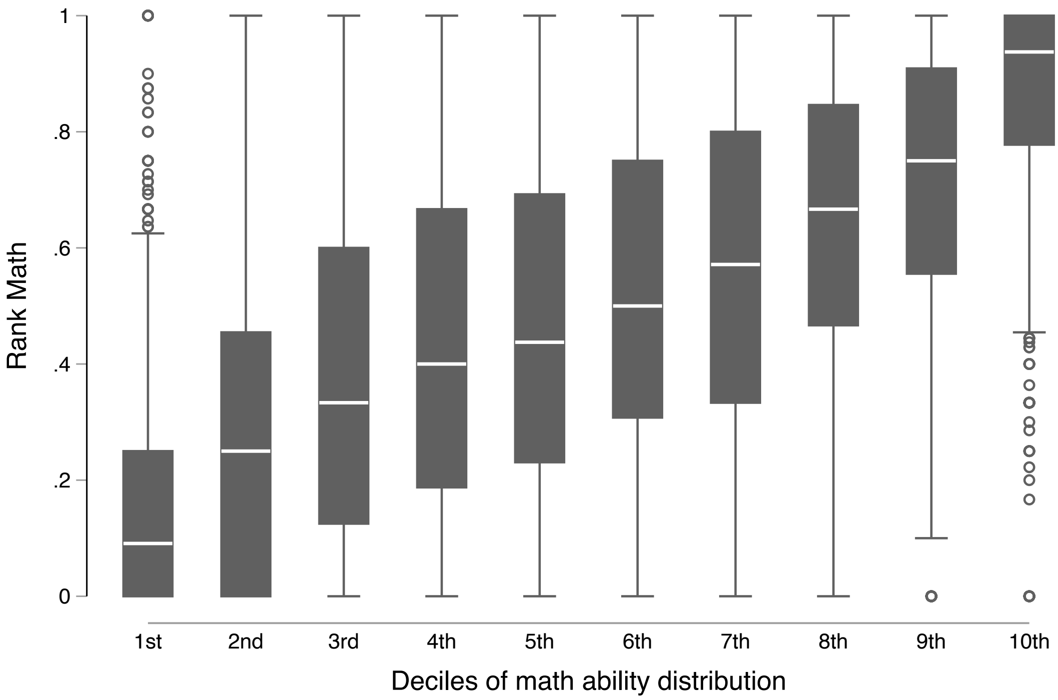
**Table 10:**
**Result: Effect on human capital investment**

| | 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 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 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.

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

**Table A5:**
**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 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 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 A6:**
**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 |

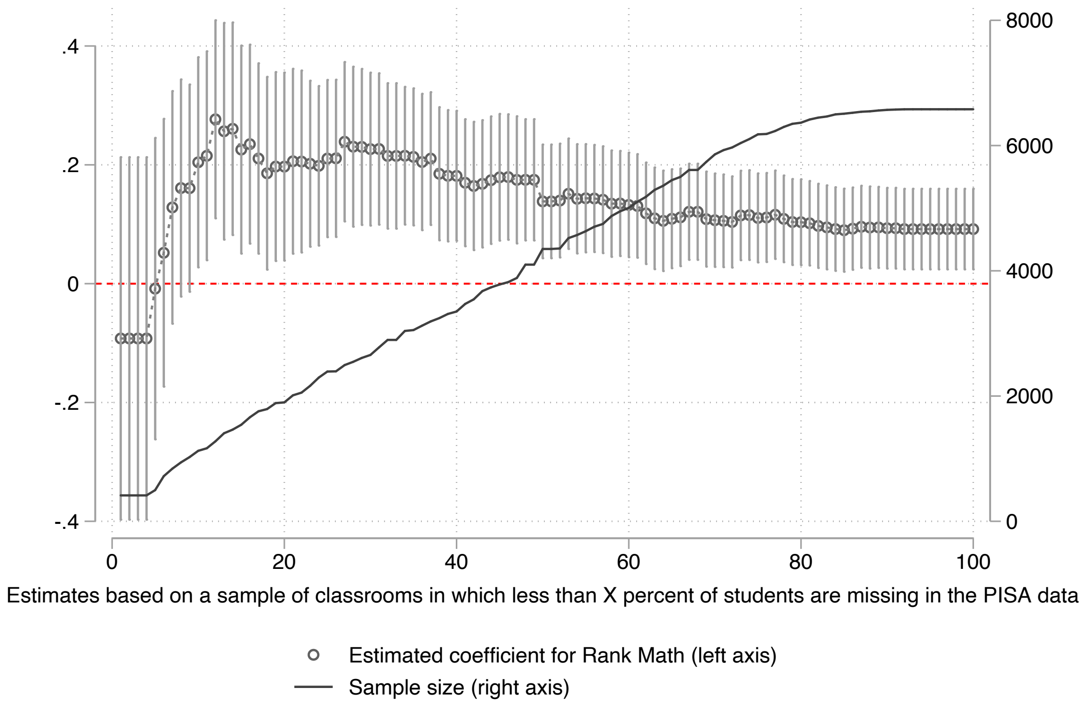
*Note:* Each column reports estimates of separate regressions of a variable indicating the STEM intensity of the first training occupation (in percent, Panel A) or a binary variable indicating if the STEM intensity of a students' first training occupation lies in the 4th quarter of the STEM intensity distribution of all training occupations (Panel B) on students classroom rank in math and/or science and/or reading (0-1, based on PISA 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 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: 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 A2:**
**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 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 A8:**
**Tercile table**

| | Lowest | Mid | Highest |
|---|---|---|---|
| Rank Math | 0.083 | 0.122* | 0.065 |
| | (0.070) | (0.069) | (0.079) |
| Observation | 2,184 | 2,237 | 2,159 |
| Cluster | 217 | 120 | 143 |

*Note:* 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 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.

**Table A11:**
**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.