Classroom rank in math and career choices*

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Abstract

We study the impact of classroom rank in math on subsequent educational and occupational choices, as well as labor market outcomes. Using the Swiss section of the PISA-2012 student achievement data linked to administrative student register data and earning records from 2012-2020, 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 training 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.

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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. Wiswall and Zafar (2015); Arcidiacono (2004); Brenøe and Zölitz (2020)).[1] An important aspect of classroom composition, that has received limited attention in the context of occupational choices, is **students** ordinal rank in the classroom.

To address this research gap, we aim to explore how a student's rank in specific subjects during compulsory schooling impacts their later career choices, income, and investments in further education. Existing research indicates that a student's classroom rank can influence their beliefs about ability and actions (e.g. Elsner and Isphording (2017); Murphy and Weinhardt (2020)). Learning about ability has been shown to be an important factor for educational and occupational choices (Arcidiacono, 2004). Since objective information on ability is often limited, students often rely on comparisons to their peers to gauge their ability. Thus, apart from actual ability, students perceived ability in a specific subject can provide incentives for selecting occupations that require skills in that particular domain (Arcidiacono et al., 2015).

We utilize a unique data set that combines the Swiss Section of the PISA-2012 student assessment test survey with longitudinal administrative records, along with new data on the skill requirements for various training occupations. Our extensive data set enables us to establish connections between a student's classroom ranking 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. Building on earlier research, which highlights the significant role of math skills in college major selection compared to other skills, our primary focus centers on a student's ranking in math and its association with the likelihood of pursuing careers in STEM fields (Arcidiacono, 2004).

In our empirical analysis, we build upon recent studies and leverage variations in the math

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

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 choices in occupations and their labor market outcomes. Furthermore, we delve into the underlying mechanisms using specific questions about subjects in the PISA-2012 background questionnaires. In particular, this allows us to explore whether the observed effects stem from students' self-perception of their math abilities and/or the level of effort they invest in the subject.

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. More specifically, we find that 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. To rule out selection concerns, we demonstrate that there is no link between classroom rank in math and choices between vocational and general education tracks after completing compulsory school.

Additionally, we observe a likely non-linear effect, with students showing a stronger response in the lower segments of the rank distribution compared to the upper segments. We also show that parental education plays a crucial role in the significance of rank effects. Students with more 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.

We further investigate the underlying mechanisms using detailed subject-specific survey data from the PISA questionnaires. Existing research suggests 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. While our data set does not allow for a direct assessment of other potential mechanisms, such as changes in teacher or parental behavior, our findings underscore the importance of students' shifts in beliefs and behaviors in the context of rank effects and their influence on occupational choices.

With a clear understanding of the link between classroom rank and career choices, we next explore the influence of these choices on students' earnings in the years following their completion of vocational education. We analyze data from tax records spanning from 2012 to 2020. Our findings reveal a positive effect of math rank on earnings. 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). These results are in line with previous research that emphasizes the positive link between the math or STEM intensity of occupations and earnings (Joensen and Nielsen, 2009). 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 allows to get self-employed.

Finally, we investigate the potential negative consequences of occupational choices based on perceived rather than actual ability for the skill match between students and training 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). Understanding the factors that contribute to skill mismatches in the labor market is of utmost importance. Fouarge and Heß (2023) have shown that students who embark on a program that doesn't align with their previously expressed preferences are more likely to discontinue their studies. In our context, a similar concern arises that decisions based on perceived rather than actual ability may lead to a misalignment between students' skills and the skill requirements of their chosen occupations. Despite the significant societal relevance of this concern, it has not been empirically tested until now.

To test this hypothesis, we utilize extensive data regarding students' enrollment status in Swiss educational institutions. This enables us to examine whether occupational choices based on rank lead to a greater likelihood of dropping out from the initial training program or switching to an occupation in a different educational field after completing the initial training program. Our analysis does not reveal any evidence supporting either of these scenarios. This absence of evidence suggests that occupational mismatches resulting from rank effects, which could potentially lead to dropout or occupational switches, are not widespread in our sample. One possible explanation for this finding could be that the increased willingness to put effort into math helps students avoid falling behind.

Relation to literature Our study adds to three important lines of research. First, it contributes 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). While much of the focus has been on general college education, there is a growing body of research investigating how program choices affect earnings differences among individuals with similar education levels (Altonji et al., 2012). These studies have identified various factors shaping educational choices, including 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 peer effects (Sacerdote, 2001; Giorgi et al., 2012). However, while much attention has been given 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). Understanding these choices is particularly important as graduates of STEM vocational education programs experience substantial earnings gains compared to other vocational programs that offer 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, including earnings and individuals' willingness to pursue further education, several years after completing their vocational education 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 peer rank on occupational choices, specifically among students in vocational education training programs. 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 invest effort even after completing their VET 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 and the resulting potential skill mismatches with job requirements, lead to lasting consequences such as dropout and occupational switches.

The rest of the paper is organized as follows. In the next section, we provide 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. In sections 5 and 6 we present the main results on education and labor market outcomes. Section 7 concludes.

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

2 Education system in Switzerland

Education is compulsory in Switzerland for students aged 4-15. Around 95% of students in Switzerland visit public schools. Public schools are 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, 2011).

The compulsory education system consists of two years of kindergarten, primary school (six years, grades 1-6), and lower secondary school (three years, grades 7-9). Starting in lower secondary school, the majority of students are tracked in accordance with their academic ability in two tracks. Roughly one third of students of each cohort are assigned to a track with basic requirements (low-track) and the other two third attends a track with extended requirements (high-track).[3] While the education system has a federal structure, hence the 26 Swiss cantons have some autonomy in education policy-making, the degree of coordination among cantons is high, and the compulsory schooling structure is roughly the same across cantons.

In the last year of compulsory school (9th grade), students can choose between mostly two types of upper secondary education.[4] Students who start a fully school-based general education program (baccalaureate schools) typically graduate within 3 years 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 Vocational education and training programs (VET). Students can choose among over 250 VET training occupations. Admission to dual training vocational education programs is market-based, i.e., training companies select and recruit students from a pool of applicants. Since very few students change tracks, both within VET programs and between VET programs and general education, the selection of a track at the upper secondary level is highly significant for career opportunities and closely connected with future income (Tuor and Backes-Gellner, 2010).

VET programs, typically lasting 2 to 4 years, teach students profession-specific practical and theoretical skills and prepare students for non-academic careers in the labor market. The majority of vocational education programs are completed in a dual training system, which combine on-the-job apprenticeships at training firms (3-4 days a week) with formal education at a voca-

[3]For a more detailed description of the Swiss education system, see, e.g., Section 2.1 in Strazzeri et al. (2022).

[4]Around 90 % of students in each cohort continue their education in upper secondary school immediately after compulsory school

tional school (1-2 weekdays). After finishing the VET program, students can start working as qualified workers or continue their education.

3 Data

3.1 Data sources

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

In our analysis, we employ the extended version of the Swiss section of the PISA-2012 wave. This extended version, as compared to the international PISA 2012 wave, incorporates additional regional samples of 9th graders, allowing us to observe a representative sample of students in their last year of compulsory school—instead of 15-year-old students—from Switzerland. Our initial sample 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 comprehensive set of background information on students and schools. Additional survey items assessed students attitudes, beliefs and preferences towards math.

We link the PISA-2012 data with three distinct data sources that allow us to investigate educational and occupational choices, as well as labor market outcomes. First, we merge the PISA data to student annual registry data from the universe of students in Switzerland covered in the LABB data (Längsschnittanalysen im Bildungsbereich) provided by the Swiss Federal Statistical Office between 2012 and 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. Individual identifiers included in the data set allow us to identify students across years and to track their educational pathways.

[5] For more information on PISA, see https://www.oecd.org/pisa.

Second, we link information on four skill requirements of training occupations (math, natural science, language, foreign language). We use information from a website, which is managed by the Swiss trade association and the Swiss Conference of Cantonal Ministers of Education and is partially funded by the Swiss Secretariat for Education, Research, and Innovation.[6] 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. These skill requirements 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. In total, the data encompasses a comprehensive array of 20 different skill measures, which can be categorized into four main groups: mathematics, natural science, native language, and foreign language.

Third, we link the PISA-2012 survey data to administrative earning records from tax data up to the year 2020.

3.2 Sample

From N students that we observe in the PISA sample, we include only students for whom we have at least one other student observation in the same classroom (i.e., we drop N observations). Further, we exclude student observations that could not be successfully linked to our two administrative data sources, e.g., because students migrated to other countries (N observations). 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, consistent with the geographical extension of French and German cantons in the country. Also, we can observe how 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. However, when looking at students character-

[6]For more information, see https://www.anforderungsprofile.ch.

istics 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.

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 1 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.

Finally, we use our detailed student register data to obtain information on students human capital investments after compulsory school. 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 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

Our variable of interest is relative classroom rank in math. In our empirical analysis, we use students' percentile rank in the classroom to measure students' ability rank. It makes sense to consider rank at the class, rather than at the school, level because this is where most interactions among students take place. 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 A2 depicts the variation in ranks based on a student's math ability across the entire sample. On average, 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 A2 offers evidence supporting this notion. In every decile of the math ability distribution, we observe 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:

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

where y_{ic} is a measure of educational or occupational choice or income 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 and measured with PISA test scores, 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. $\boldsymbol{X_{ic}}$ is a vector of student i's background characteristics (sex, age, parental education, nationality, migration status, language spoken at home), and ϵ_{ic} represents an error term. Additionally, we add a set of fixed-effects, δ_c.

Our identification strategy relies on variation in the classroom composition of students' math ability, which determines idiosyncratic variations in students' math rank. In order to identify the causal effect of math rank, the math rank has to be as good as randomly assigned. This means, that we need a conditional independence assumption (CIA).

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

In essence, this assumption implies that ϵ_{ic} is uncorrelated with a student's ordinal math rank given their own math ability, personal attributes, and a set of classroom fixed effects. These classroom fixed effects are pivotal for establishing causality. They are incorporated to 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.

4.1 Challenges to Identification

The two most important concerns regarding the identification of rank effects are that i) students ordinal rank is (even under random classroom assignment) cross-sectionally correlated with other features of the classroom and ii) that we do not have random classroom assignment in our setting. We now describe how our approach tackles these challenges in more detail. We present a set of sensitivity analysis regarding the choice of our estimation model in Section 5.5.

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.

Both parents and children may choose schools, and more specifically, select into particular classrooms based on the anticipated rank in the math distribution. If students are sorted into schools or classrooms based on these factors, there is a risk of omitted variables bias. To control for any 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.[7]

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

4.1.1 Balancing test

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 primary treatment variable and other peer-related variables. If the conditional independence assumption holds true, predetermined characteristics should exhibit no correlation with rank. Each cell in Table A9 represents a regression of our treatment variable (ordinal ranks of students in math) or another variable, which should be quasi-randomly assigned (peer ability and variation in peer ability), against predetermined student characteristics, along with a second-order polynomial in ability and classroom fixed effects. Our results indicate that most characteristics are unrelated to our treatment variables, 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 the coefficient magnitude is small. In summary, we do not observe meaningful imbalances in observable characteristics and so assume the remaining variation in rank to be orthogonal to unobservable factors that determine our outcomes. However, to safeguard against potential violations of the CIA we control for all student characteristics in our main specification. In Section 5.5 we show that our specification choice is robust against several alternative specifications.[8]

4.1.2 Residual variation

A natural question is how much variation is left in our rank variable after conditioning on our set of control variables and classroom fixed effects. In Figure A3 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, because of the different test-score distribution in each given class. This variation exists because classes are small and achievement distributions differ. We complement this illustration by assessing the raw and conditional variation in our treatment variable across different parts of the math ability distribution. In Table A3 we show 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

[8] Since we use a reduced sample of students selecting into VET program in several specifications we show in Table A10 that the balancing test looks very similar when using the reduced sample of students selecting into VET programs.

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.

5 Results

In this section, we provide estimates of the impact of ordinal rank on both occupational and educational choices. All of our results account for classroom fixed effects, individual-level controls, the absolute ability level of each student by utilizing a second-order polynomial function based on their corresponding PISA score, and standard errors clustered by school and track.

5.1 Occupational choices

We begin our analysis by examining the impact of students' ordinal rank in math on the STEM intensity of their chosen training occupation. Table 6 presents our findings. The dependent variable is a binary measure denoting the STEM intensity of an occupation. We define a training occupation as STEM-intensive if it falls within the upper quartile of the STEM intensity distribution of all training occupations, signifying a STEM intensity exceeding 67.37%. To calculate the STEM intensity distribution, we rely on the skill requirement measures available for each occupation.[9]

In Column 1 of Table 6, 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 SD increase in classroom rank in math corresponds to a 3 percentage point rise in the likelihood of choosing a STEM-intensive training occupation, equivalent to a 13% increase relative to the sample mean (Table A4).

To demonstrate the specificity of our findings to students' subject-specific classroom rank

[9]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 5.5.

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 mandatory schooling. In particular, the dependent variable is set to 1 if a student pursues one of the following paths within a year after finishing compulsory education: a vocational education track (Panel A), a general education track (Panel B), or whether they do not enroll in upper secondary school (Panel C). We estimate Equation 2 using a rank measure based on PISA scores in math (Column 1).

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.[10]

[10] 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.

5.2 Effect asymmetries

In our primary estimations, we utilized a linear specification. However, several studies have suggested that rank effects may not necessarily follow a linear pattern (e.g., Gill et al., 2019; Denning et al., 2021), while others have found limited evidence for nonlinear effects (Delaney and Devereux, 2021). To explore the potential presence of nonlinear effects, we extend our analysis by replacing the linear subject rank variables with indicator variables for each tercile of the rank distributions, with the second tercile serving as the reference category. The results, shown in Table A15, 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.

We extend our analysis of effect asymmetries by examining whether positive or negative deviations of classroom ranks from global ranks have differential impacts on occupational choices. To distinguish between positive and negative deviations, we compute the global rank of students using all individuals in our sample, and then compare students with classroom ranks above or below the global rank. In Table A12, we present our findings. Column (1) displays our baseline result from the first column of Table A1, indicating that math ranks significantly influence occupational choices. Subsequently, we investigate the causal effect of a negative deviation of the classroom rank from the global rank that a student could anticipate. Column (2) demonstrates that negative deviations decrease STEM choices. Column (3) further delves into the interaction between ranks and negative deviations by regressing our indicator of STEM choices on an indicator for negative deviations and the interactions of ranks with indicators for positive and negative deviations. Rank effects appear more pronounced for students experiencing negative deviations compared to those experiencing positive deviations, resembling our baseline estimate in column (1). However, the difference between positive and negative deviations is not statistically significant at conventional levels ($p = 0.39$).

5.3 Heterogeneity

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 pattern is similar in Switzerland.[11] 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 A16. 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 A16 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 A16, 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.

5.4 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

[11] Apart from the distribution of the STEM intensity measure, Figure 1 shows the corresponding percentage value of female trainees in the occupation (right axis). The bimodal density function in Figure 1 shows that female vocational education students are more likely to select into occupations with lower STEM intensity.

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. 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 4 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, which in turn influences their willingness to put effort into the subject (as shown in Column 1 and Column 8). This positive association between subject-specific ranks and effort 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).

5.5 Robustness checks

In Section 5.1, our analysis was 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 A1 and Table A2, 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 A1) or a 1 math intensity measure (Table A2). 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 A6 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.

Another potential concern relates to the specific sampling procedure used in the PISA data. The PISA data doesn't always include all students in each classroom that we observe. Therefore, our rank measure is constructed using information on all students in the class in some cases, while in other cases, it relies on a random sample of students according to the PISA data. In Figure A1, 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 vocational programs. Therefore, our results are unlikely to be significantly affected by the sampling procedure.

Another concern is that parents may select schools based on the rank that their children would have, violating our assumption that the rank is as good as randomly assigned. In Table A10 we have shown that our rank measure is uncorrelated with several student background characteristics including parental education and a proxy for the socioeconomic status, but of course cannot completely rule out other unobserved parental background characteristics to be correlated with our treatment variable. We think that this unlikely to be an issue for two main reasons. First, 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. Second, we follow Kiessling and Norris (2023) and show that the size of the rank effect does not differ by average school ability (Table A13).

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 human capital. We categorize distributions of student achievement into groups based on distribution characteristics (e.g., mean and variance) and interact indicators for these groups, with our control variables for a student's math ability. In Table A11 we show that our results are robust to the inclusion of these interactions.

A final concern might be the existence of a specification error that is correlated with our treatment variable. If human capital has a different relationship to future outcomes across cantons but is modeled as having the same relationship, this would introduce error into the model. To ensure the robustness of our results regarding a specification error, we explore various alternative specifications in Table A14 in which we change the way how 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 Labor market outcomes

In this section, we delve into whether classroom rank in math yields lasting impacts on individual labor market outcomes beyond the influence on selection into specific occupational training programs. We initiate our investigation by examining the association between classroom rank and earnings in the years following compulsory education in 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 delve into the potential implications for occupational mismatch.

6.1 Earnings

Figure 2 provides a summary of our estimation results using yearly income as the dependent variable. Each dot in Figure 2 represents coefficient estimates (β) derived 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 2a presents results estimated on the sub-sample of students who choose a vocational education training program. For completeness, Figure 2c displays results for the non-VET sub-sample, while Figure 2b presents the results on the entire sample.

In Figure 2a, we observe a positive and slightly increasing impact of our rank measure on yearly income starting in the year 2015. For the period spanning 2016-2020, the estimated coefficient falls within a range of 1,748 to 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.

Figure 2b, displaying estimation results for the full sample, depict 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 majority of this group may only enter the labor market in 2020. Figure 2c illustrates the resulting lack of association between our treatment and earnings for the non-VET students sub-sample.

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 landscape characterized by relatively modest wage differentials both between and within training 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 7 summarizes our estimation results on overall income across the entire span of our data set. Panel B of Table 7 reports estimation results on overall income specifically for the years post-graudation 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, particularly for students transitioning from compulsory education into vocational education tracks (VET). 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.[12]

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 US. 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 do also matter apart from the occupational choice.

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

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

education and training (VET) program. Table 8 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 8 reveals that studentrs 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.[13] We also distinguish between investments in the same educational field as the student's initial VET program (Panel B) and investments in different fields of education (Panel C).

We do not observe an increase in the time allocated to college education, instead we 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 significant step towards self-employment (Panel B).

6.3 Mismatch

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 be non efficient. Students making decions 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 inquire whether classroom rank in math may have has negative consequences for persistence rates within the chosen occupation. This would suggest that students with higher math rank might overestimate their ability and opt for occupations for which they are not ideally suited.

[13]Define professional education ...

To assess this hypothesis, we employ two measures of occupational persistence. First, we examine the time spent within training occupations in diverse educational fields as opposed to the student's initial training occupation choice. Second, we employ a binary measure indicating dropout from the chosen vocational education and training (VET) program. In Panel C of Table 8, 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 an 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 A6, 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, lead to mismatches in the labor market resulting in dropout from the initial occupational choice. This finding does not imply that the observed matches between students and occupations are necessarily efficient. In fact, it could be that classroom rank in math also has a positive association with the willingness to provide subject-specific effort, offsetting potential negative consequences of decisions based on perceived ability.

7 Conclusion

This paper delves into the influence of students' classroom rank in math on their occupational choices and labor market outcomes. Recognizing that relative rankings are intrinsic to social environments, we explore the consequences of relative math ability on critical life decisions.

Our empirical analysis shows compelling evidence that a higher classroom rank in math is significantly associated with an increased likelihood of selecting a STEM-focused vocational program. These occupational choices bear lasting consequences in the labor market. We show that students with a higher math classroom rank substantially outperform their peers in terms of income several years after completing compulsory schooling. Additionally, we provide evidence that classroom ranks influence students' subsequent outcomes by altering their perceived ability and willingness to put in effort. This translates into higher investments in educational programs after compulsory education. Furthermore, we find that parental education serves as a mitigating factor in the impact of ranks on students' choices.

In contrast to an exclusive focus on individual career perspectives, we adopt a broader labor market perspective to examine whether rank-based decisions contribute to horizontal mismatches within the labor market. Our findings indicate that while classroom rank in math influences students' occupational choices, this influence does not results in hightened dropout rates from vocational education and training (VET) programs. Furthermore, these choices do not require supplementary re-education in different educational fields. This could be attributed to the increased effort exerted by students, helping to alleviate potential negative effects of occupational mismatch.

Our study underscores the crucial role of the classroom environment, specifically students' math rank, in shaping not only their occupational choices but also their subsequent income levels. We also propose that changes in students' behavior and beliefs serve as potential mechanisms for these observed effects. These findings emphasize the importance of considering social dynamics within educational settings when evaluating students' career decisions.

Furthermore, our research provides valuable insights into the phenomenon of occupational mismatch. Contrary to initial expectations, we find no evidence for the hypothesis that rank effects lead to occupational mismatches, where students find themselves in occupations misaligned with their abilities or preferences. This suggests that, notwithstanding the influence of rank effects, students continue to make appropriate occupational choices aligned with their skills and interests.

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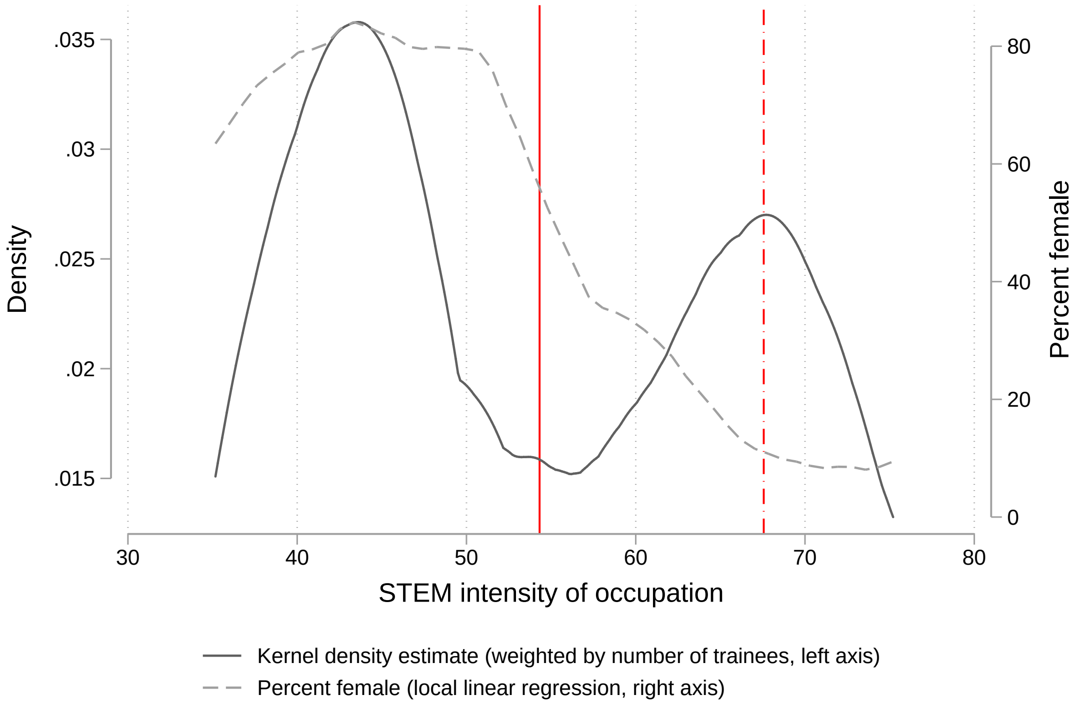
TABLES AND FIGURES

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 1:
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 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

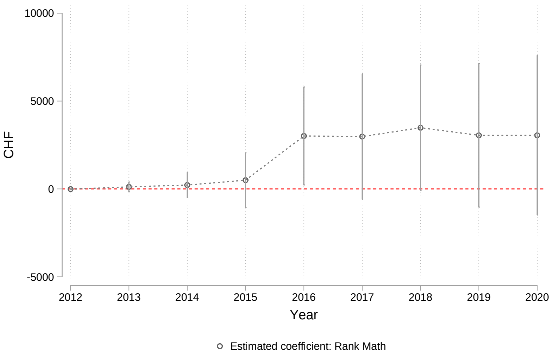
Note: Each column reports estimates of separate regressions of a binary variable indicating whether a student enters a vocational education program (Panal A) or a general education program (Panel B) or no program (Panel C) within one year after compulsory school on students' classroom rank in math and/or 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:
Result: Effect on selecting a STEM occupation

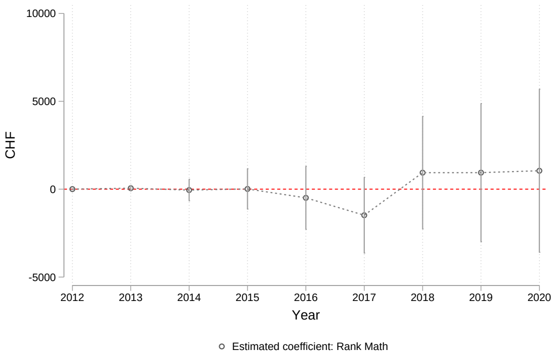
	(1)	(2)	(3)	(4)
Rank Math	0.092**			0.089**
	(0.041)			(0.043)
Rank Reading		0.015		-0.003
		(0.039)		(0.042)
Rank Science			0.022	-0.026
			(0.041)	(0.045)
Controls	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes
Observation	6,580	6,580	6,580	6,580
Cluster	480	480	480	480

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.

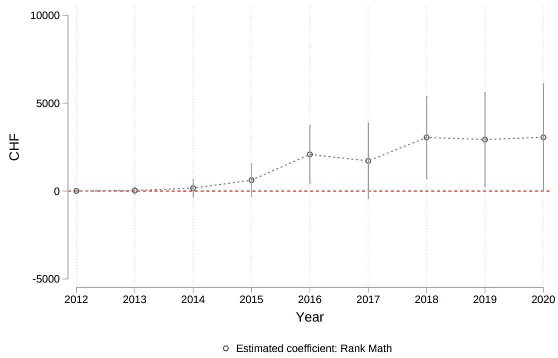
Figure 2:
Results: Effect on income



(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 7:
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 8:
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

Table A1:
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 A2:
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 A3:
Variation in ranks

	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
Observation	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx

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.

Table A4:
Robust: 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: Robust standard errors are clustered at school-times-track level.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A5:
Robust: Result continuous and definition stem

	(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)
B: 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: Robust standard errors are clustered at school-times-track level.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A6:
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: Robust standard errors are clustered at school-times-track level.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A7:
Robust: Effect on overall earnings (rank reading)

	Subsample		
	VE students	Others	All
	(1)	(2)	(3)
A: Earnings 2012-2020			
Rank Reading	8852.625	4812.326	8805.473
	(9339.761)	(8648.408)	(6124.261)
B: Earnings 2016-2020			
Rank Reading	6713.518	3462.298	7015.515
	(8703.258)	(8019.541)	(5610.618)
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 reading 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 reading. Robust standard errors are clustered at school-times-track level.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A8:
Robust: Effect on overall earnings (rank science)

	Subsample		
	VE students	Others	All
	(1)	(2)	(3)
A: Earnings 2012-2020			
Rank Science	3484.350	3588.768	6152.870
	(9750.956)	(9453.401)	(6500.853)
B: Earnings 2016-2020			
Rank Science	4234.878	2950.231	5881.388
	(8983.081)	(8780.959)	(5971.077)
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 science 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 science. Robust standard errors are clustered at school-times-track level.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A9:
Balancing test full sample

	Rank measure		Peer ability (mean)		Peer ability (SD)	
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.009*	0.002	-1.570*	-0.160	1.298***	-0.054
	(0.005)	(0.003)	(0.939)	(0.106)	(0.398)	(0.148)
Female	-0.096***	-0.010***	17.851***	0.004	-0.194	0.188
	(0.005)	(0.003)	(0.943)	(0.154)	(0.307)	(0.173)
Swiss nationality	-0.037***	0.000	7.872***	0.045	0.463	-0.241
	(0.008)	(0.005)	(1.443)	(0.229)	(0.570)	(0.261)
Language spoken at home: Swiss	-0.047***	0.003	10.126***	-0.191	0.043	-0.025
	(0.009)	(0.005)	(1.615)	(0.266)	(0.627)	(0.316)
Parental education	-0.044	-0.004	8.445	0.013	0.353	0.145
	(0.006)	(0.003)	(1.028)	(0.148)	(0.400)	(0.162)
More than 200 books at home	0.13	0.17	0.15	0.14	0.12	0.12
	()	()	()	()	()	()
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:
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A10:
Balancing test VET sample

	Rank measure		Peer ability (mean)		Peer ability (SD)	
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.002	0.006*	-0.003	-0.005	-0.003	0.008
	(0.003)	(0.003)	(0.002)	(0.004)	(0.009)	(0.013)
Female	-0.010***	-0.009**	0.000	-0.000	0.011	-0.004
	(0.003)	(0.004)	(0.002)	(0.005)	(0.010)	(0.014)
Swiss nationality	0.000	0.006	0.001	-0.000	-0.014	-0.006
	(0.005)	(0.006)	(0.004)	(0.008)	(0.015)	(0.024)
Language spoken at home: Swiss	0.003	0.003	-0.003	-0.011	-0.001	-0.013
	(0.005)	(0.006)	(0.004)	(0.010)	(0.018)	(0.023)
Parental education	-0.004	-0.000	0.000	0.003	0.008	-0.003
	(0.003)	(0.004)	(0.002)	(0.005)	(0.009)	(0.013)
More than 200 books at home	0.001	0.000	-0.005*	-0.016**	0.022**	0.011
	(0.004)	(0.006)	(0.003)	(0.007)	(0.011)	(0.022)
Ability controls	Yes	Yes	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	VET	All	VET	All	VET

Note:
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A11:
Robustness: ability interact

	(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:
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A12:
Asymmetric shocks

	(1)	(2)	(3)
Rank Math	0.092**		
	(0.041)		
Negative Shock		-0.035**	-0.037
		(0.015)	(0.023)
Rank Math x Negative Shock			0.089*
			(0.054)
Rank Math x Positive Shock			0.053
			(0.049)
Controls	Yes	Yes	Yes
Class FE	Yes	Yes	Yes
P-val (no het)			0.39
Observation	6,580	6,580	6,580
Cluster	480	480	480

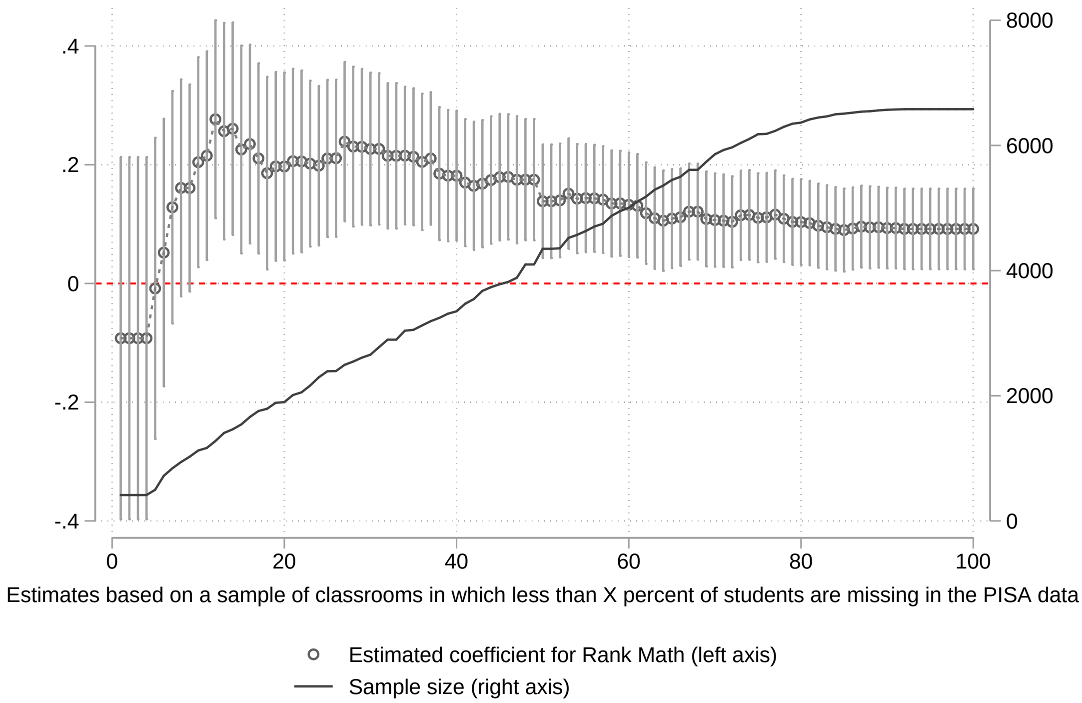
Note:
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A13:
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:
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Figure A1:
Robustness: Students missing from classroom



Note: Each dot reports estimates of our baseline effect of students' classroom rank in math on occupational choice (Table 6, 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 A14:
Robust: Ability controls

	(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: Robust standard errors are clustered at school-times-track level.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A15:
Robust: 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

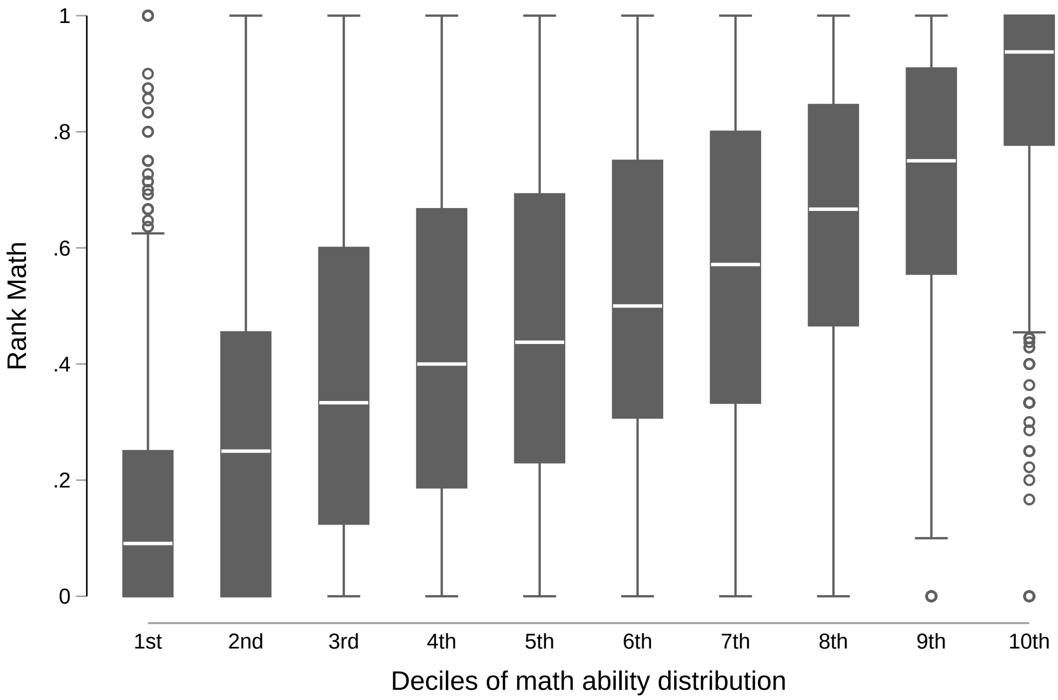
Note: Robust standard errors are clustered at school-times-track level.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A16:
Robust: Het

	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

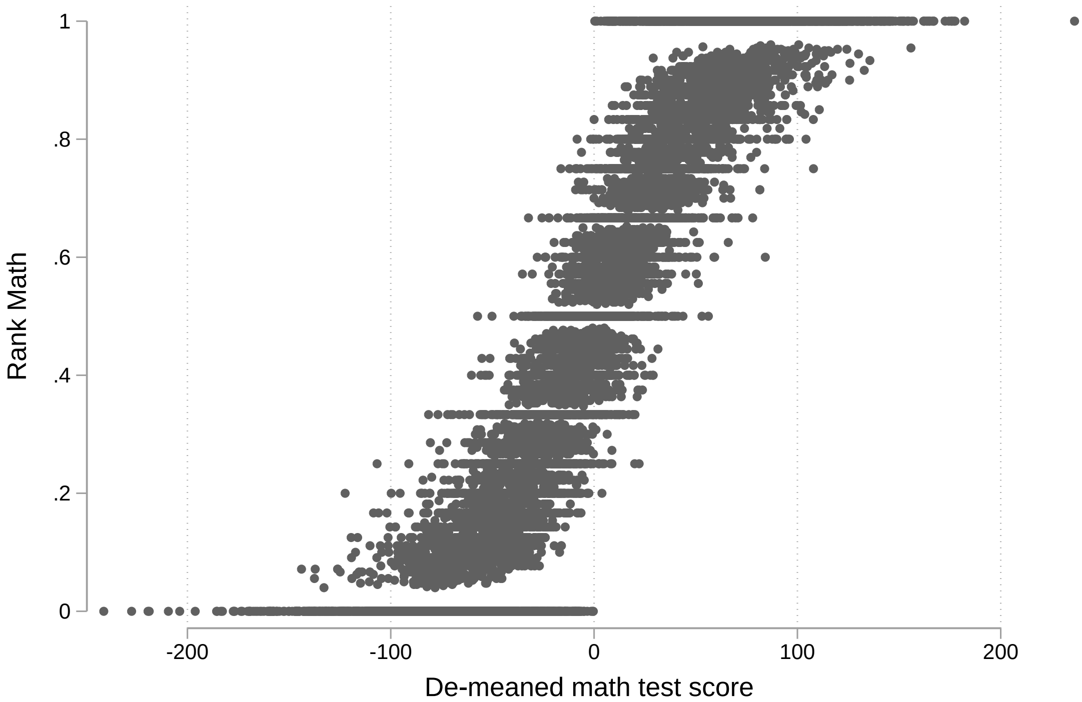
Note: Robust standard errors are clustered at school-times-track level.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Figure A2:
Global versus local rank (cf. Elsner/Isphording)



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.

Figure A3:
Distribution of rank measure across classrooms (cf. Murphy/Weinhardt)



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