Brief Exposure to Female STEM Professionals and Students' Trajectories in College

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Abstract

I study two large-scale role model interventions that expose Swiss high school students to talks by STEM professionals during single-day school events. Combining data on more than 1,500 speakers with administrative records on all Swiss high school graduates, I find that exposure in the final year of high school increases STEM college enrollment by 4.1% and STEM degree completion within six years by 7.7%. Events with a higher share of female speakers have larger effects for both female and male students. Presentation style explains part of these effects: female speakers are more likely to use interactive formats, to which students respond positively. Accounting for interactivity reduces the female-speaker effect by 37%.

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1 Introduction

Women remain substantially underrepresented in STEM fields, with negative implications for talent allocation, innovation, and economic growth (Goldin, 2014; Hsieh et al., 2019; Bertrand, 2020). A large body of evidence shows that sustained exposure to female role models, such as teachers, advisors, or political leaders, raises girls' participation in male-dominated fields (Beaman et al., 2009; Carrell et al., 2010; Card et al., 2022). Motivated by this evidence, role model interventions seek to generate similar effects through much briefer exposure: female professionals visit class rooms as guest speakers and share their experiences with students in a short talk. Although such interventions offer a light-touch and potentially scalable way to increase female students' participation in male-dominated fields, evidence on whether they work—and why they work—remains limited (Bertrand and Duflo, 2017).

This paper provides novel evidence on the impact of role model interventions and the role of speaker gender. I draw on two large-scale interventions in high schools in Switzerland: *ETH unterwegs*, by ETH Zurich, and *Tecdays*, by the Swiss Academy of Engineering Sciences. Both interventions aim to encourage high school students to pursue STEM in college by exposing students to single-day events at their schools, during which students attend multiple career talks by STEM professionals. I link detailed data on the events and more than 1,500 participating speakers to administrative records that track the college trajectories of all students graduating from Swiss high schools between 1999 and 2019.

Three features of the setting allow me to go beyond existing evidence. First, the interventions have taken place since 2006 and have reached more than 80,000 high school students across Switzerland, allowing me to assess long-run effects and scalability. Second, both female and male STEM professionals give talks at the events, generating event-level variation in the share of female speakers students encounter. I leverage this variation to study the effectiveness of female speakers relative to male speakers. Finally, the large number of speakers and rich speaker data let me separate the effect of speaker gender from other attributes, such as presentation style, speaker quality, and content.

The first part of the paper estimates the average effect of event exposure on students' later STEM participation. I exploit variation in the timing of events across schools in an event-study design, comparing outcomes in college for students graduating from high school in the years before and after an event, in schools with and without an event. The identifying assumption is that—after controlling for school and graduation-year fixed effects—STEM participation would have evolved in parallel across schools with and without an event, in the absence of the event. To support this assumption, I analyze detailed annual school reports and find no evidence for confounding school-level changes, such as other STEM activities or career events, correlated with hosting an event. To further strengthen identification, I restrict the main analysis to schools that host at least one event, noting that the effect sizes in this sample are slightly smaller than those observed in the full sample. Finally, I verify that there are no significant differences in pre-event trends of the outcomes studied.

The events increase high school students' STEM participation in college, and the effects persist. The probability of enrolling in STEM in college increases by 0.91 percentage points for cohorts exposed to an event in their high school graduation year, representing a 4.1% increase. These cohorts are also 1.11 percentage points more likely to obtain a STEM degree within six years of high school graduation, reflecting a 7.7% increase. Additionally, I find comparable gains for students attending an event before early track choices in high school, and no detectable effects for cohorts exposed in years without major educational decisions. Finally, consistent with its stated objective, *ETH unterwegs* increases STEM enrollment specifically at ETH Zurich.

The results are robust to different approaches of addressing the potential negative weighting of the two-way fixed effects estimator (Goodman-Bacon, 2021). First, I apply the diagnostics by De Chaisemartin and d'Haultfoeuille (2020) and find that none of the weights in my main specification are negative. Second, following the estimation procedure by Sun and Abraham (2021), I combine the event-study parameters for each school with equal weights and find effects comparable to the baseline specification. Finally, using a stacked approach

as in Cengiz et al. (2019) and Dube et al. (2025), I find that the results are robust to using only untreated schools as controls.

The second part of the paper exploits variation in the event-level gender composition of speakers to examine whether female speakers are more effective than male speakers. I rely on the assumption that the variation in the share of female speakers across events is exogenous. I show that the female-speaker share is not systematically correlated with observable school- or event-level characteristics, supporting the identification strategy. My main estimation splits events along the median female-speaker share in each intervention. The results replicate for each intervention and are robust to alternative exposure measures.

Events with a high share of female speakers substantially increase STEM enrollment for both female and male students. Female students exposed to such events increase STEM enrollment by 2.11 percentage points, while STEM enrollment among male students increases by 1.94 percentage points. The effects persist and students are more likely to obtain a STEM degree in college after attending an event with a high share of female speakers. In contrast, events with a low share of female speakers have no detectable effects for either group. Consequently, I do not find any differential effect of increasing the share of female speakers by student gender.

Previous research often attributes the effect of female speakers to a role model mechanism, where female speakers inspire female students through their shared gender, with minimal impact on male students. The positive effect on male students observed in this study suggests that speaker gender may proxy for other omitted attributes of speakers that matter for students' choices.

Consistent with this interpretation, I provide evidence that presentation style explains a meaningful part of the estimated female-speaker effect on students' STEM choices. For more than 4,000 presentations, I digitize short presentation descriptions and classify their content with a large language model, validating the classification against hand coding and student presentation feedback. I find that female speakers are more likely to use interactive formats

that involve active participation, collaboration, and supportive presentation tools, and that events with a higher share of interactive presentations generate larger increases in STEM participation. Accounting for interactivity reduces the estimated female-speaker effect by 37 percent and renders it statistically insignificant. Complementing these results, I show that the effect of interactivity is not exclusively tied to female speakers: events with a high share of interactive presentations but a low share of female speakers are as effective as similarly interactive events with a high share of female speakers. Furthermore, speakers recognized with awards for excellent teaching—an external measure of speaker quality uncorrelated with speaker gender—also increase STEM participation for both female and male students.

I examine alternative mechanisms that could account for the stronger effects of female speakers. First, female speakers present different topics than their male counterparts: they are more likely to give talks related to female-dominated or gender-balanced STEM fields, and students exposed to events with a higher female-speaker share are more likely to enroll in those fields. However, controlling for topic composition does not attenuate the estimated female-speaker effect, and increasing the share of presentations in these fields does not by itself raise the overall impact of the events. Second, while I cannot rule out that male students' response is partially driven by alternative mechanisms such as marriage-market motives, I present descriptive evidence that both male and female students are more likely to cite interactivity as a positive feature in feedback to presentations by female speakers. Finally, I show that the results are not explained by other observable speaker characteristics, such as age, seniority, or speaker experience.

Taken together, the results show that brief role model interventions can have a substantial impact on students' long-run educational outcomes, and that part of the greater effectiveness of female speakers relative to male speakers reflects differences in presentation style. This suggests that effects operating through gender alone may be smaller than previously thought. At the same time, selecting or training speakers to deliver more engaging presentations has the potential to broaden the pool of potential role models, which may be particularly valuable

in settings where women face higher demands for non-promotable service work (Babcock et al., 2017).

This paper makes two main contributions. First, it contributes to a large literature that uses the gender of political leaders, advisors, teachers, or speakers as a proxy for same-gender role-model effects (Bettinger and Long, 2005; Dee, 2005; Beaman et al., 2012; Carrell et al., 2010; Bertrand and Duflo, 2017; Lim and Meer, 2017, 2020; Card et al., 2022; Canaan and Mouganie, 2023; Gallen and Wasserman, 2023). Closest to this study, Porter and Serra (2020), Breda et al. (2023), and Patnaik et al. (2024) experimentally examine role model interventions, but study interventions with either exclusively female professionals or few speakers overall. I build on this work by showing that part of the estimated female-speaker effect in brief role model interventions reflects differences in presentation style rather than speaker gender alone. These results align with lab evidence from social psychology that role model characteristics beyond gender matter significantly (Cheryan et al., 2011; Betz and Sekaquaptewa, 2012; Bertrand and Duflo, 2017).

Second, the paper extends a literature on the determinants of students' STEM participation by showing that brief in-person interventions with STEM professionals can increase both STEM enrollment and STEM degree completion in college, a key finding to assess their welfare implications. Existing studies in this literature focus on factors such as teachers or peers (Lavy and Sand, 2018; Carlana, 2019; Brenøe and Zölitz, 2020; Mouganie and Wang, 2020), family dynamics (Anelli and Peri, 2019), course exposure (Ellison and Swanson, 2010; Joensen and Nielsen, 2016; Card and Payne, 2021), and summer programs (Cohodes et al., 2022). While this work highlights the importance of early and sustained exposure, I show that a one-day intervention close to high school graduation can successfully nudge students into STEM in college, including students who were not previously pursuing a STEM specialization.

The remainder of this paper is organized as follows. Section 2 describes the context, and Section 3 presents the data used in the analysis. Section 4 outlines the empirical strategy.

Section 5 presents the overall results on students' STEM participation following event exposure. Section 6 and 7 examine variation by speaker gender and investigate the mechanisms behind the observed effects. Section 8 concludes.

2 Setting

In this section, I briefly summarize the key features of the events studied in this paper and the institutional background in which they take place.

Events I examine the impact of two event series: *ETH unterwegs* organized by the Swiss Federal Institute of Technology (ETH Zurich) and *Tecdays* by the Swiss Academy of Engineering Sciences. *ETH unterwegs* events are aimed at promoting STEM among high school students and introducing them to specific STEM study fields available at ETH Zurich. Presentations are delivered by speakers from ETH faculty, typically focus on a topic related to their research, and occur over the course of a school day. On the day of the event, there are no classes and all students across all grades of a school must attend the presentations. On average, a presentation lasts 45 minutes, and students attend six presentations per event sequentially. For the 107 *ETH unterwegs* events that are part of the analysis, 262 unique speakers participated in the events, with 7% of speakers being women.

Tecdays are similarly aimed at promoting STEM among high school students but do not focus on a specific university. Speakers come both from academia and the private sector. Furthermore, in contrast to *ETH unterwegs* events, students specify the sessions they are interested in attending. From an average of 45 sessions that are offered per event, students select 6 preferred sessions before the event and are then allocated to 3 sessions. Each session lasts for 90 minutes, and 1,252 unique speakers participate in the 76 *Tecdays* that are part of the analysis. 22.8% of *Tecdays* speakers are women.

Two event features are particularly relevant to my analysis. First, the events take place in an annually changing set of high schools. I observe events at 83 out of the 142 high schools

in Switzerland. Second, students across all grades in participating schools are required to attend, enabling me to analyze the impact of the events across student cohorts that are exposed to the events at different points in time relative to their high school graduation.

Institutional background The events take place within the Swiss academic high school system, designed to prepare students for tertiary education. Typically, students enter academic high school at age 14, following lower secondary school. Depending on the canton, students either select a specialization track at this point or at a later stage. Two tracks emphasize STEM subjects (physics and math, and biology and chemistry), while the other tracks focus on languages, economics, law, and the arts. Admission to Swiss academic high school is selective, contingent on either lower secondary school grades or success in an entry exam. Approximately 25% of all students attend academic high school.

In the final year of high school, students must register by the end of April for their tertiary program and university of choice if they intend to commence studies immediately after graduating high school. Students already have to select their college major at this point, before they start their tertiary studies.

Two features make this setting particularly suited to study the impact of the events. First, graduating from academic high school guarantees access to all universities and tertiary study programs, without any grade restrictions or the ability of universities to select students (except for medical and sports studies). Second, all universities and tertiary study programs require a similar low semester fee. Together, these features allow me to observe students' unrestricted preferences for study programs.

On average, 17,000 students graduate from 142 academic high schools each year, with 56.8% of the graduates being female. Approximately 50% of graduates proceed directly to university, while an additional 40% start their tertiary studies after a gap year.

3 Data

This paper combines two main sources of data: records on STEM promotion events and Swiss administrative education records. The event records identify when and where events took place, provide detailed information on speakers and presentations, and comprise post-event feedback surveys. The administrative data allow me to follow the universe of high-school graduates from exposed high schools through tertiary education. This section describes each source and defines the main variables used in the analysis.

3.1 Event Data

I assemble a new presentation-level dataset from event flyers collected from ETH Zurich and the Swiss Academy of Engineering Sciences for all *ETH unterwegs* and *Tecdays* events held between the start of the two series in 2006 and 2007, respectively, and the end of the 2019/20 school year. The resulting dataset contains 183 events, approximately 1,500 speakers, and 5,000 presentations.

The flyers report the event date, host school, speaker names, presentation titles, and, for *Tecdays*, short presentation descriptions. I digitized these materials and converted them into structured data at the presentation-level. Figures A1 and A2 show example flyers.

3.1.1 Speaker characteristics

Speaker gender. I infer speaker gender from first names using data from the Swiss Federal Statistical Office on the gender-specific frequency of first names in the Swiss population. To assess the accuracy of this procedure, I compare inferred gender for ETH-affiliated speakers with administratively recorded gender from ETH Zurich and find that all speakers are correctly classified.

Speaker experience. Many speakers participate in multiple events. I therefore construct a measure of prior event experience that counts, for each speaker appearance, the cumulative

number of presentations that the speaker delivered before that event.

***ETH unterwegs*-specific speaker characteristics.** For speakers at *ETH unterwegs* events, I observe additional characteristics from ETH Zurich administrative records. First, I recover speakers' birth years and compute age at the time of event participation. Second, I identify whether a speaker has received ETH Zurich's Golden Owl teaching award, which is awarded annually on the basis of student evaluations. Third, I proxy seniority using the titles listed on the flyer, coding whether the speaker is identified as a professor.

***Tecdays*-specific speaker characteristics.** For speakers at *Tecdays*, I classify the employer listed on the flyer as either a private-sector employer or a research institution using publicly available information on the organization.

3.1.2 Presentation characteristics

Presentation topic. I classify presentation topics using presentation titles. The classification follows the International Standard Classification of Education (ISCED) fields (UNESCO, 2015), which makes the presentation-level measures directly comparable to tertiary field-of-study choices in the administrative data.

***Tecdays*-specific presentation characteristics.** For the approximately 4,000 *Tecdays* presentations, the flyer includes a short description of the presentation. I use these descriptions to construct measures of presentation characteristics. The coded characteristics are derived from the guidance provided by the Swiss Academy of Engineering Sciences to prospective speakers and capture whether a presentation emphasizes active student participation, student collaboration, supportive materials or tools, student creativity, links to students' personal experiences, specific career paths, and theoretical concepts.

I code each dimension separately using a large-language-model classifier applied to the presentation descriptions. The exact prompts, coding protocol, and model details are re-

ported in Appendix A. To assess classification quality, I compare classifier-generated labels to hand-coded labels in a validation subsample for two of the interactivity-related dimensions. Relative to the hand-coded benchmark, the classifier achieves 91.6% precision and 78.5% recall.

Independently of the classification method, a central concern is whether the short presentation descriptions succeed in capturing meaningful features of the presentations as delivered at the events. To examine this, I link the coded descriptions to post-presentation student feedback collected by the Swiss Academy of Engineering Sciences. After each *Tecdays* event, students complete a survey that asks what particularly impressed them about each presentation. I code these open-ended responses into the same set of presentation dimensions using the same large-language-model classifier. The feedback data cover 38 events and contain 29,775 responses from 9,484 students on roughly 1,500 presentations.

If the description-based measures capture meaningful presentation attributes, then a dimension coded from the description should predict whether students mention that same dimension in their feedback on the corresponding presentation. Appendix Table A3 provides regression results that tests for such a relation. For each dimension, the corresponding measure from the presentation description is positively and statistically significantly associated with the same dimension in the student feedback.

3.2 Swiss Administrative Data

I link the event data to student-level administrative records covering the universe of Swiss high-school graduates and their subsequent tertiary education careers based on the school and date of the event. Events take place throughout the Swiss academic year, which runs from mid-August to mid-July. Because high-school students must apply to tertiary programs by April 30 of their final year, I assign events to academic years using April 30 as the relevant cutoff for exposure.

The administrative records allow long-run tracking of postsecondary choices and degree

completion for complete graduation cohorts. I focus on two main outcomes.

STEM enrollment. The first outcome is an indicator equal to 100 if a student enrolls within two years of high-school graduation in a STEM field at a tertiary institution, and 0 otherwise. I use a two-year enrollment window to ensure comparability across cohorts. Field-of-study classifications follow ISCED. I define STEM fields as ISCED-05 (natural sciences, mathematics, and statistics), ISCED-06 (information and communication technologies), and ISCED-07 (engineering, manufacturing, and construction).

To distinguish across types of STEM fields, I further classify fields according to female representation. Fields in which women account for less than 40% of enrolled students are defined as predominantly male STEM fields; fields with a female share of at least 40% are defined as gender-balanced or predominantly female STEM fields. Related classifications are used by Brenøe and Zölitz (2020) and Anelli and Peri (2019). Table A1 lists the study fields in each category, and Figure A3 illustrates the raw enrollment series and event timing for one school.

STEM graduation. The second outcome is an indicator equal to 100 if a student completes an undergraduate degree within six years of high-school graduation in a STEM field at a tertiary institution, and 0 otherwise. I define STEM graduation using the same ISCED-based field mapping as for STEM enrollment.

3.3 Summary Statistics

Table I reports summary statistics for the analysis sample. The presentation-level data cover all 183 STEM promotion events held between the 2006/07 and 2019/20 academic years.

ETH unterwegs comprises 950 presentations, of which 11.9% were delivered by female speakers. Speakers are, on average, 45.2 years old; slightly more than half hold a professor title, and 12.7% have received an award for excellent teaching. Roughly one-fifth of presentations cover STEM fields with predominantly female or gender-balanced student bodies.

Tecdays comprises 4,015 presentations, 22.7% of which were delivered by female speakers. Speakers work overwhelmingly outside academia. About 24.8% of presentations cover predominantly female or gender-balanced STEM fields, and 44.7% of presentations involve active student participation.

The main student sample includes 239,299 graduates from the 83 high schools that hosted at least one event during the sample period, covering cohorts graduating between the 1999/00 and 2019/20 academic years; 57.6% of these graduates are women. For cohorts graduating in 2007 or later, the administrative data also report students' high-school specialization. Among female students, 22.7% graduate from a STEM specialization track, compared with 42.9% of male students. In the postsecondary data, 14.4% of female graduates and 33.0% of male graduates enroll in a STEM field within two years of high-school graduation.

4 Empirical Strategy

I conduct the analysis at the student level, estimating whether attending a STEM event increases the probability that student i graduating from school s in school year t enrolls in or graduates from a STEM program in college.[1] As the baseline specification, I estimate a dynamic event-study two-way fixed effects (event-study TWFE) regression. This design allows me to check for differential trends before a STEM event and after all exposed students have graduated. It also enables me to identify when the effect materializes, which is particularly important given that students across all grade levels attend the events and schools experience multiple events.

The event-study specification takes the following form:

$$Y_{ist} = \sum_{j=-4}^{5} \beta_j Event_{st}^{j} + \gamma Event_{st}^{(-20,-5)} + \delta Event_{st}^{(6,13)} + \mu_s + \theta_t + \epsilon_{ist}, \tag{1}$$

where Y_{ist} represents the STEM enrollment and degree outcomes in college. The events in

[1] Each student i occurs in the data exactly once.

my setting correspond to a staggered, non-absorbing treatment, where schools can be treated multiple times. Out of the 142 schools, 59 host no event, 30 host one event, and 53 host two or more events. For schools hosting multiple events, $Event_{st}^{j}$ equals 1 if a student graduates j years from any event and 0 otherwise, where j ranges from four years before to five years after an event.

I restrict this dynamic effect window by including binned endpoints: $Event_{st}^{(-20,-5)}$ equals the number of future events at school s for students graduating from school s more than four years before an event, and $Event_{st}^{(6,13)}$ equals the number of past events at school s for students who graduate from school s more than five years after an event. The specification therefore controls for all other possible events at school s that have occurred in the past or will occur in the future. Table A2 illustrates the data structure and coding of the respective parameters.

Finally, μ_s and θ_t represent school and graduation-year fixed effects, respectively. To address serial correlation in the error term ϵ_{ist}, I adjust standard errors for clustering at the school level. Taken together, the specification compares the probability of enrolling in STEM in college for students graduating from high school before and after an event, in schools with and without an event.

After tracing the event effects dynamically, I estimate a static two-way fixed effects (static TWFE) regression that is informed by the dynamic results:

$$Y_{ist} = \beta_0 Event_{st}^{0} + \gamma Event_{st}^{(-20,-2)} + \delta Event_{st}^{(1,13)} + \mu_s + \theta_t + \epsilon_{ist}. \tag{2}$$

In this specification, the main parameter of interest is $Event_{st}^{0}$, which equals 1 for students who attend an event and graduate in the same year and 0 otherwise. $Event_{st}^{(-20,-2)}$ equals the number of future events for students graduating from high school more than one year before an event, and $Event_{st}^{(1,13)}$ equals the number of past events for those who graduate more than one year after an event. μ_s and θ_t represent school and graduation-year fixed effects, respectively. As I control for all graduation cohorts two years before an event and

all cohorts in the years after an event, the omitted comparison period consists of students who graduate in the academic year immediately before an event.

The specification requires two key assumptions to causally identify the effects of the events. First, schools should not adjust their behavior in anticipation of a future event (*no anticipation*). Second, after controlling for school and graduation-year fixed effects, STEM enrollment in schools with and without an event would move in parallel in the absence of an event (*parallel trends*). A potential violation of this assumption would occur if STEM events were systematically correlated across schools with other changes affecting the probability of STEM enrollment (i.e., school principals might organize other activities in the same year as the events that equally increase students' STEM enrollment).

To assess the validity of the identification assumptions, I conduct an analysis based on 244 detailed school calendars taken from annual school reports, available for 26 schools (see Figure A4 for an example). The results, presented in Table II, show a significant positive effect of 0.89 on the likelihood that a report mentions a *Tecday* or *ETH unterwegs* event in the year the event occurs. However, there are no effects on the likelihood that schools organize other STEM activities or host any career or study information events in the same year. Furthermore, *ETH unterwegs* events increase STEM enrollment specifically at ETH Zurich, further supporting the assumption that there are no school-level changes correlated with the events of interest.

Additionally, I restrict the analysis to the 83 schools that hosted at least one event. As this in turn can lead to issues with the TWFE estimator (Baker et al., 2022), I show in Table IV that the results are consistent but slightly more conservative than the results based on all 142 schools or a specification that only uses untreated schools as controls. Finally, I use the event-study specification to demonstrate the absence of differential trends in STEM enrollment probabilities across schools before a STEM event.

A third assumption, motivated by De Chaisemartin and d'Haultfoeuille (2022) and Dube et al. (2025), is that the dynamic effects stabilize after a certain point (*effect stabilization*),

which is particularly relevant when using non-absorbing treatments as the repeated events in this study. Section 5 presents evidence consistent with this assumption. I show that the treatment effect emerges immediately for students who attend an event in the year they face an educational choice (such as graduation or specialization choice), and I find no effects on other graduation cohorts. I also provide evidence that the results are robust to using untreated control schools as well as alternative ways of dealing with multiple events in a school.

Finally, econometric literature has identified potential issues about using TWFE estimators when treatment is staggered, treatment effects are heterogeneous, and there are dynamic treatment effects over time (Goodman-Bacon, 2021; Sun and Abraham, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Baker et al., 2022; Dube et al., 2025). In this setting, the immediacy of the effects would cause me to anticipate minimal TWFE biases (Baker et al., 2022). Indeed, as shown in Section 5, my results are not subject to negative weighting and are robust to alternative estimators and control groups.

5 STEM Participation Across All Events

5.1 Dynamic Event-Study Results

Figure 1 presents estimates from the event-study TWFE specification in equation (1), showing the trend in the probability of STEM enrollment for students graduating in the years preceding an event. Notably, this trend is flat, with point estimates close to zero.

By contrast, STEM events result in an immediate spike in the probability of STEM enrollment in college following an event for students who attend an event close to deciding either their college major or their specialization in high school. Specifically, the probability of enrolling in STEM in college increases by 0.91 percentage points (p-value: 0.04) or 4.1% for students who attend an event and graduate from high school in the same year as the event.

There is a similar effect for students who attend an event and choose their specialization track in high school in the same year. As shown in Table A4, the secondary effect for students graduating from high school three to four years after attending an event is concentrated at the 34 high schools in the sample that allow students to choose their specialization after entering the school (in the other 49 high schools, students select school and track simultaneously).[2] Similarly, Table A5 shows that the point estimates on the likelihood of selecting a STEM track in high school and the likelihood of enrolling in STEM in college are positive (but insignificant) for students who attend an event shortly before making their specialization choice.

In contrast, the events do not influence students who attend an event but are not close to any educational decision. The impact of the events on students who attend an event and graduate one to two years later is close to zero (–0.18 percentage points, p-value: 0.73). This aligns with prior research indicating that information tends to be most effective when delivered at the time of decision-making (Bleemer and Zafar, 2018; Patterson et al., 2019; Dynarski et al., 2021).

Finally, the effect fades away for students graduating five or more years after an event. Given that high school typically lasts four years in most schools within the sample, these students have usually not yet been enrolled at the schools and thus have not attended the events. This serves as a placebo test, suggesting that the events are not associated with more fundamental changes in the schools hosting an event.

The *ETH unterwegs* events focus on introducing high school students to the STEM study fields available specifically at ETH Zurich. Panel (b) of Figure 1 focuses on the impact of the events on the probability of enrolling in STEM at ETH Zurich. Similar to the effects on overall STEM enrollment, students attending an event in either the year of high school graduation or before their specialization choice are significantly more likely to enroll in STEM

[2]The effect in Figure 1 materializes in multiple lags because both school duration and timing of track choice vary between schools, while the figure displays the effects of the events relative to high school graduation.

at ETH Zurich (0.77 percentage points, p-value: 0.01; 0.99 percentage points, p-value: 0.01, respectively).

Moving forward, I focus on the more precisely estimated effect on students who attend an event and graduate in the same year, using equation (2).

5.2 Static DiD Results

Table III, column (1) displays the results from the static TWFE specification in equation (2) for students who graduate in the year of an event. The estimate is positive, statistically significant, and comparable in magnitude to the estimates obtained from the more flexible event-study TWFE specification. Given that the administrative data allow me to follow students through college, I explore whether students persist in their chosen study field in college. This is an important step, as previous studies analyzing brief interventions with STEM speakers could only analyze students' enrollment decisions rather than their study success.

Table III, column (3) presents the effect of the events on the likelihood of obtaining an undergraduate degree in a STEM field in the six years after high school graduation. Students who attended an event are 1.11 percentage points (p-value: 0.02) more likely to obtain an undergraduate degree in a STEM field, representing a 7.7% increase. In percentage terms, the events have a slightly stronger effect on STEM graduation than on STEM enrollment, indicating that students who are induced by the events to pursue STEM studies are at least as successful as those who pursue STEM in college in the absence of an event. I also corroborate the findings on obtaining a STEM degree in the dynamic event-study setting, displayed in Figure A7.

Columns (2) and (4) allow the effects to differ by student gender by interacting each event indicator with a dummy for male students. In these specifications, the coefficient on $Event^{(0)}$ captures the effect for female students, while the interaction term $Gender:\ Male \times Event^{(0)}$ captures the difference between male and female students. For STEM enrollment (column

(2)), the estimated effect for female students is 0.72 percentage points. The estimated male–female difference is 0.52 percentage points, implying a male point estimate of 1.24 percentage points, but the interaction is imprecisely estimated and not statistically significant. For STEM degree completion (column (4)), the estimated effect for female students is 0.86 percentage points, significant at the 10% level, and the estimated male–female difference is 0.62 percentage points, again statistically insignificant. Overall, the gender-interacted specifications provide no evidence that the impacts differ by student gender.

I further investigate the impact of the events by student gender, by distinguishing between predominantly female or gender-balanced STEM fields and predominantly male STEM fields. Figure A8 shows that a gendered pattern emerges when I segment STEM study fields by the gender mix of students within those fields. Female students exhibit a significantly higher likelihood than male students of enrolling in gender-balanced or predominantly female STEM study fields. Conversely, male students are significantly more likely to enroll in predominantly male STEM study fields.

I next examine in Table A6 which study fields the STEM events affect students away from, focusing on business and law, the arts and humanities, education, the social sciences, and health sciences. The results suggest that most substitution occurs from health studies, though the size of the point estimate cannot fully account for the increased enrollment in STEM, suggesting that students are also nudged away from fields such as the social sciences. STEM promotion events also do not influence students' probability of enrolling in business and law, arts and humanities, and education.

Finally, Table A7 reveals that the impact of the events on students who attend an event and graduate from high school in the same year is driven by students who specialized in non-STEM tracks during high school. This finding aligns with the interpretation that students who did not specialize in STEM tracks may have less accurate or less well-informed beliefs about pursuing STEM studies at the college level prior to attending the events.

5.3 Robustness

In settings where treatment is staggered, treatment effects are heterogeneous, and there are dynamic treatment effects over time, the TWFE estimator is a weighted average of heterogeneous group-specific treatment effects where the weights may be negative, leading to potential bias (Dube et al., 2025). The bias arises because previously treated units are implicitly used as controls for newly treated units, though they may still be experiencing lagged time-varying and heterogeneous treatment effects.

To address concerns regarding these potential biases, I conduct several robustness tests. To calculate the weights associated with each event, I employ the diagnostics recommended by De Chaisemartin and d'Haultfoeuille (2020). Figure A9 reveals minimal variation in the weights, with none being negative in the baseline specification. Following the approach of Sun and Abraham (2021), I then combine event-study parameters for each school with equal weights. The results, presented in Table IV, column (2), show a 0.91 percentage point increase in the probability of enrolling in STEM (p-value: 0.01), which closely aligns with my baseline estimate of 0.95.[3]

Moreover, I confirm that the results are not contingent upon the selection of schools with events as control schools, supporting the assumption that the effects of the events are transient. In Table IV, column (3), I extend the estimation sample to schools without any event, and in column (4) I implement a stacked event study with clean controls similar to Cengiz et al. (2019), where each event receives a separate stack and only schools without any event serve as control schools. Importantly, my baseline specification yields similar but more conservative estimates than these two regressions that use untreated schools as controls.

The results are robust to alternative ways of addressing outcome dynamics within schools with events. First, the events increase STEM enrollment by 0.96 percentage points when I include linear school-specific time trends to the baseline specification (column (5)). Second, the effects do not change when I implement a simple DiD specification in which I include

[3]Figures A5, A6, and A7 replicate the dynamic results following this estimation procedure.

only students from treated schools who graduate just before and after an event (column 6). Furthermore, column (7) shows that all students who have attended an event and graduated in the years following an event are allocated to the control group. The results remain significant and similar to the baseline specification.

Finally, to show that the reported effects are not artifacts of the TWFE specification itself, I conduct permutation inference and randomly assign STEM events across years in 1,000 replications. Figure A9 illustrates that the reported effects based on the true data fall outside the range of estimated placebo effects.

6 Exposure to Female Speakers

The results so far show that the probability of enrolling and graduating in STEM in college increases after attending a STEM event. In the following, I use quasi-random event-level variation in female-speaker share to empirically investigate whether female speakers are more effective than male speakers at increasing students' STEM participation.

6.1 Variation in the Share of Female Speakers

I examine whether the share of female speakers at the event level is not systematically correlated with other event- or school-level characteristics. Figure A10 shows the distribution of events by female-speaker composition, which ranges from 0% to 40% for *ETH unterwegs* and from 22.5% to 38.64% for *Tecdays*. Building on the discussion in Section 4, the empirical strategy aimed at identifying the effect of female speakers relies on the assumption that the variation in the share of female speakers across events is as good as random.

This assumption would be violated if event organizers systematically assign a higher share of female speakers to specific schools, such as those with a larger share of female students or a stronger initial STEM focus. Likewise, school leadership invested in supporting female students in STEM may seek to influence event organizers to schedule more female speakers

at their schools. Additionally, organizers may adjust other event characteristics alongside the share of female speakers.

In interviews, the event organizers for each intervention reported that they rely on a pool of potential speakers for the events. Once a year, the event organizers invite potential speakers from that pool to sign up for speaker slots at the events scheduled for that year, and subsequently speakers sign up based on their individual availability. These availability constraints generate the variation in the share of female speakers across the events that I analyze. The organizers also noted that they had never tracked the gender composition of speakers, nor had they attempted to increase the share of female speakers for specific events. As a result, variation in the share of female speakers should be unrelated to school- and event-level characteristics.

In Table A8, I examine the correlation between the share of female speakers and various event- or school-level characteristics. Events with a high share of female speakers are indeed not systematically targeted to schools with a higher share of female students or to schools with a stronger initial STEM focus, both in terms of tracks offered and students' pre-event STEM participation in college. In addition, events with a high share of female speakers are not more likely to take place in a particular language region of Switzerland, occur at different times during the school year, or involve a greater number of speakers. Overall, these patterns support the identifying assumption.

To examine the effects of female speakers on STEM participation, I divide events into those with a low and high share of female speakers by the median female-speaker share in each intervention, treating the share of female speakers as indicating different treatment dosages (Callaway et al., 2024). *ETH unterwegs* events with a high share of female speakers comprise all events with a female-speaker share larger than 9.1%, *Tecdays* with a high share of female speakers comprise events with a share of female speakers larger than 22.4%.

6.2 Results

Figure 2 replicates the dynamic event study shown in Figure 1 but distinguishes between events with a low and a high share of female speakers. I find that events with a high share of female speakers have a significantly larger effect on students' STEM enrollment. Students who attend an event with a high female-speaker share and who graduate in the same year are 1.76 percentage points (p-value: 0.005, 7.90%) more likely to enroll in STEM, while events with a low female-speaker share do not have any detectable effect on STEM enrollment (–0.43 percentage points, p-value: 0.45, –1.95%). In the corresponding static specification shown in Table A9, I find that the effects persist through the undergraduate level: students who have attended an event with a high share of female speakers are 1.64 percentage points (p-value: 0.04, 11.4%) more likely to obtain a STEM college degree.

Figure 3 splits the sample by student gender and differentiates between predominantly male and predominantly female or gender-balanced STEM fields. Female students attending events with a high share of female speakers exhibit a 2.11 percentage point increase in the likelihood of enrolling in STEM (p-value: 0.004, 14.65%). They are also more likely to enroll in predominantly male STEM fields. However, the effect is mainly attributed to increased enrollment in predominantly female STEM fields (1.72 percentage points, p-value: 0.01). The estimates for low-share events are not significant and tend toward negative values (–0.85 percentage points, p-value: 0.20).

Similarly to female students, male students are significantly more likely to enroll in STEM after attending events with a larger share of female speakers. Specifically, they are 1.94 percentage points (p-value: 0.04, 5.89%) more likely to enroll in STEM after attending high-female-share events, compared with 0.11 percentage points (p-value: 0.91) for low-share events. This positive effect is driven by greater enrollment in predominantly female STEM fields: male students who attend low-share events exhibit a 1.54 percentage point decrease (p-value: 0.02), whereas those at high-share events show a 0.71 percentage point increase (p-value: 0.14). The difference is significant at the 0.01 level.

Figure A11 combines the results for female and male students to directly examine the impact of increasing the share of female speakers on the gender gap in STEM enrollment among high school graduates. If these events are effective at reducing the gender gap in STEM, then the female STEM conversion rate would increase more than the total STEM conversion rate, resulting in a positive effect. However, the primary finding in Figure A11 is the absence of any detectable treatment effect on the gender gap for either type of event.

6.3 Robustness

Table A10 shows that the positive relationship between female-speaker exposure and subsequent STEM enrollment is robust to alternative specifications and measures of exposure. The same pattern of stronger effects of high-share events appears for both *ETH unterwegs* and *Tecdays* events when analyzed separately. Using a continuous measure of female-speaker share yields a similarly positive estimate: a one-standard-deviation increase in female-speaker share raises STEM enrollment by 1.29 percentage points. Finally, measuring exposure by the number of female speakers rather than their share produces a comparable pattern, with a statistically significant difference between high- and low-exposure events (p-value: 0.022).

7 Mechanisms

In this section, I explore why events with a larger share of female speakers increase students' likelihood of enrolling in STEM. Previous literature has suggested that the absence of a positive effect of female speakers on male students supports a female role-model mechanism, in which female speakers inspire female students through shared gender. The positive effect of events with a high share of female speakers on male students suggests that female and male speakers might also influence students' study choices through distinct non-gender characteristics that are correlated with speaker gender.

First, I examine whether female and male speakers differ across other non-gender char-

acteristics that may influence student outcomes. To do so, I extract structured information from a unique sample of 4,000 presentation descriptions by applying ChatGPT, as described in Section 3. The data reveal that female and male speakers do indeed differ in their presentation styles. I then proceed to demonstrate that these presentation characteristics have a measurable impact on students' study choices.

Do female and male speakers differ? I examine whether observable speaker or presentation characteristics correlate with speaker gender. The results, presented in Figure 4, show that female speakers are on average slightly younger than their male counterparts, are less likely to hold a professor title, participate less frequently in the events, and are more likely to work in academia than in the private sector. However, there is no significant difference between female and male speakers in terms of having received a teaching award granted by ETH Zurich based on student surveys.[4]

Turning to presentation attributes, I identify significant differences between female and male speakers. Categorizing presentations with the ISCED classification system, I find that female speakers are more likely to present in predominantly female or gender-balanced STEM fields. Furthermore, they tend to adopt more interactive presentation methods, including encouraging collaboration among students, fostering active participation, and using supportive presentation tools. They are also more likely to reference specific career paths during their presentations. In contrast, male speakers are more inclined to focus on theoretical models or concepts. Importantly, the reported differences between female and male speakers remain, even after controlling for the specific STEM field the presentation relates to.

Do these differences matter? In this section, I examine the impact of speaker and presentation characteristics, for which differences between female and male speakers were observed, on students' likelihood of enrolling in STEM fields. Figure A13 illustrates the ef-

[4]The likelihood of receiving an award is lower for female faculty (2.81%) compared to male faculty (3.68%) in a given year.

fects of separately increasing the proportion of presentations delivered by younger speakers, more experienced speakers, those in predominantly female or gender-balanced fields, and presentations characterized by a more interactive presentation style. To identify presentations with an interactive presentation style, I group the dimensions active participation, use of supportive presentation tools, and student collaboration together.

When categorizing events by the proportion of presentations in female-friendly STEM fields, I find no significant differential effect on STEM enrollment. This suggests that differences in presentation topics alone do not fully account for the positive impact of female speakers. Similarly, increasing the share of younger or more experienced speakers does not result in a significant positive effect on students' STEM participation. In contrast, events featuring a high share of interactive presentations have a significantly greater impact on students' STEM enrollment compared to those with a lower share of such presentations.[5]

I corroborate this finding with an analysis of students' presentation feedback surveys, administered by the Swiss Academy of Engineering Sciences. The analysis draws on surveys from 38 events, comprising 29,775 responses from 9,484 students. In these surveys, students answer an open-ended question about what particularly impressed them in each presentation. I classify the answers using ChatGPT, as described in Section 3, and measure which presentation characteristics are more likely to be mentioned in feedback to female instead of male speakers. The results, shown in Figure A14, indicate that both female and male students are significantly more likely to highlight interactive features in presentations by female speakers than in those by male speakers.

Do the observed differences explain the estimated female-speaker effect? After establishing that female and male speakers differ in their likelihood to deliver interactive presentations and that events with a high share of interactive presentations have stronger effects on STEM enrollment, I examine whether this pattern can explain the previously es-

[5]Table A11 shows that observables are balanced across events with a high and low share of interactive presentations.

timated effect of female speakers. Table V presents the results for *Tecdays*, the subset of events for which presentation descriptions are available. In column 1, *Tecday* events with a high female-speaker share increase the probability of STEM enrollment by 2.73 percentage points (p-value: 0.058), relative to events with a low female-speaker share. Once I control for whether an event featured a high share of interactive presentations, this estimate falls to 1.73 percentage points (p-value: 0.159), a reduction of 37%, while the coefficient on a high interactive-presentation share is 2.52 percentage points (p-value: 0.031). Adding further controls for other presentation characteristics reduces the coefficient on high female-speaker share relative to low female-speaker share to 1.34 percentage points (p-value: 0.349), whereas the coefficient on interactive presentations remains positive at 2.78 percentage points (p-value: 0.056). Column 4 shows that these two dimensions are not additive. Both a high female-speaker share and a high interactive-presentation share are positively associated with STEM enrollment when considered separately, but their interaction is negative and statistically significant (-4.47, p-value: 0.043). This pattern suggests that female-speaker share partly proxies for presentation style: events with more female speakers are more effective in part because they are more interactive, and the marginal contribution of either characteristic is offset when the other is already present.

What is the impact of interactive male speakers? Finally, I explore whether interactive male speakers have effects on students' STEM participation similar to those of female speakers. I proceed in two steps. First, I divide *Tecday* events by both their female-speaker share and their share of presentations with an interactive style. Figure A12 shows that the larger effects of events with a high share of interactive presentations is driven by both low- and high-female-speaker-share events. This pattern is consistent with the results in Table V, which suggest that interactive presentation style predicts higher STEM enrollment beyond speaker gender.

Second, I use information on whether ETH faculty speakers participating in *ETH un-*

terwegs received the Golden Owl award for excellent teaching at ETH Zurich, an external measure of speaker quality that is not correlated with speaker gender. At the end of each spring semester, ETH Zurich's student association surveys enrolled students and asks them to rate their lecturers' teaching on a 10-point scale. Based on these evaluations, one lecturer per department is selected for the award. I collected data on all 251 awardees since the award's introduction in 2005 and identify those who also participated in *ETH unterwegs* between 2005 and 2020. Figure 5 shows that events with a high share of speakers recognized for excellent teaching increase STEM enrollment for both female and male students, with significantly larger effects than events with a low share of such speakers.

8 Conclusion

In this study, I examine the effect of role model interventions with STEM professionals on high school students' subsequent STEM participation in college using an event-study design. I find that high school students who are exposed to these interventions when they are facing consequential educational decisions increase their STEM enrollment in college and are more likely to obtain a STEM college degree in the long run. A high share of female speakers at the events increases STEM participation both for female and male students. Leveraging rich information on speaker-student interactions, I find that a meaningful portion of the estimated effect of female speakers can be attributed to female STEM professionals more frequently using an interactive presentation style. Further analysis suggests that interactive male speakers have a comparable effect on students' STEM participation.

These results have two important implications. First, since this paper shows that role model interventions can operate through channels beyond the effects of shared gender, such initiatives do not necessarily narrow the STEM gender gap between female and male students. Instead, focusing on long-term interactions between students and potential role models such as teachers may be a more promising strategy to reduce gender gaps. Second, role

model interventions are an effective tool to increase students' overall STEM participation, and increasing the proportion of engaging speakers in such initiatives can amplify this effect. While focusing on female speakers is one way to identify such speakers in the setting studied, selecting or training speakers to deliver engaging presentations may be preferential when considering other constraints, such as an already greater demand for academic service responsibilities by female faculty (Babcock et al., 2017; Guarino and Borden, 2017).

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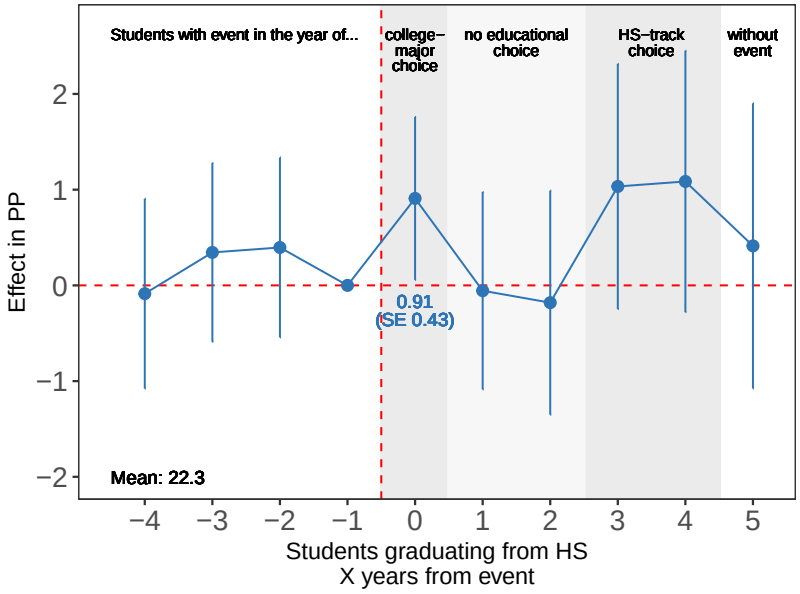
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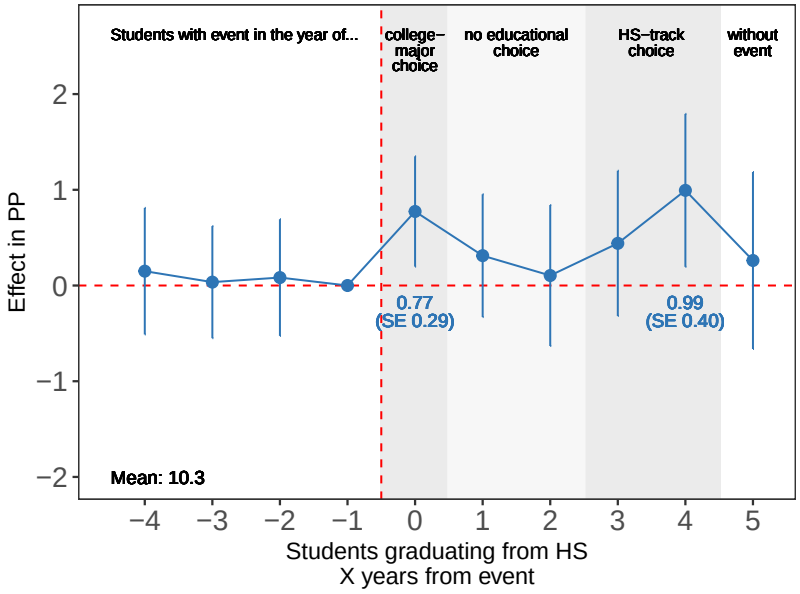
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Figures



(a) STEM



(b) STEM at ETH Zurich

Figure 1: Impact of STEM Events on the Probability of Enrolling in STEM in College

Notes: The figure shows the results from the event study in equation (1). The figure exploits 183 STEM promotion events between 2006 and 2019. OLS coefficients with the 95% confidence interval (vertical lines) based on standard errors clustered at the school level are displayed. Figures A5 and A6 in the Appendix replicate the results following the estimation procedure by Sun and Abraham (2021).

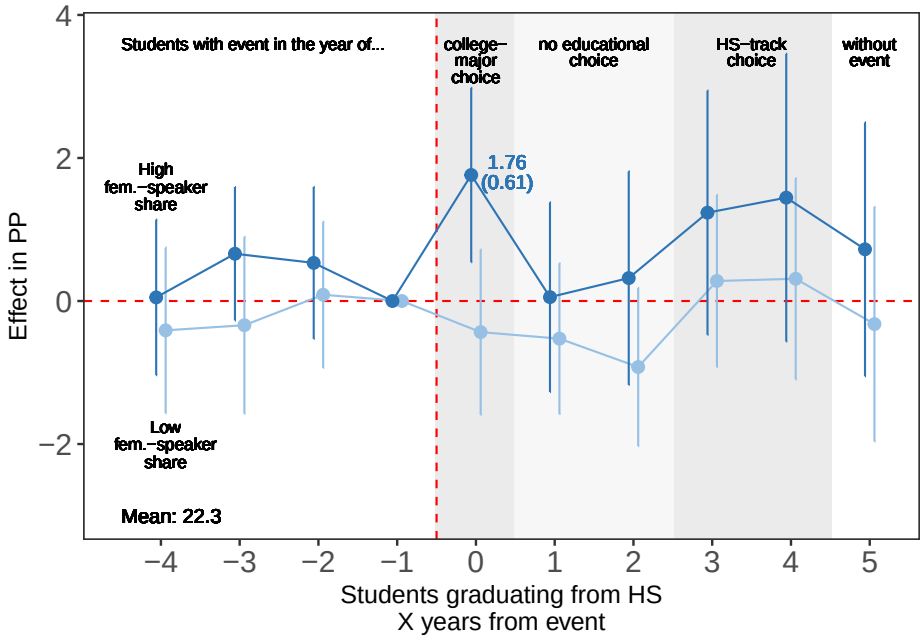


Figure 2: Impact of STEM Events With a High Share of Female Speakers on the Probability of Enrolling in STEM in College

Notes: The figure shows the results from the event study TWFE analysis as in equation (1), exploiting 183 STEM promotion events between 2006 and 2019. In contrast to figure 1, the figure shows the effect of events with a high share (blue) versus a low share (light blue) of female speakers on the likelihood that a student enrolls in STEM in college after graduating from high school. OLS coefficients with the 95% confidence interval (vertical lines) based on standard errors clustered at the school level are displayed.

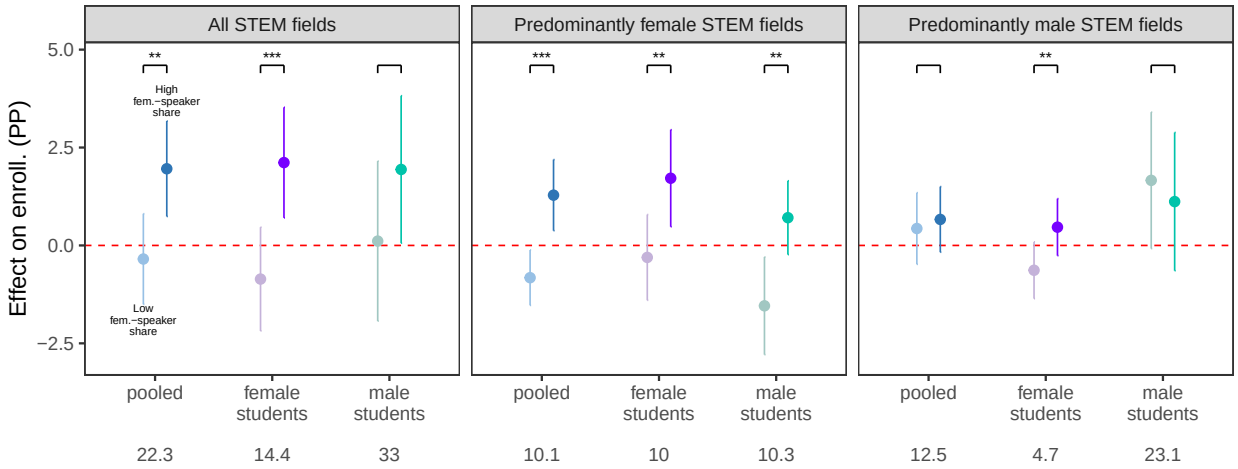


Figure 3: Impact of Event-Level Variation in Female-Speaker Share on STEM Enrollment

Notes: The figure presents the results for the analysis of changes in speaker composition based on equation (2), exploiting 183 STEM promotion events between 2006 and 2019. The figure shows the effect of an event, depending on its female-speaker share, on the likelihood that a student enrolls in STEM in college after graduating from high school. The effect of an event on the students who attend an event and graduate from high school in the same year is shown. STEM is separated into predominantly female or gender-balanced (female share $>$ 40%) and predominantly male fields. OLS coefficients with the 95% confidence interval (vertical lines) based on standard errors clustered at the school level are displayed. Significance levels of differences: * p$<$.1, ** p$<$.05, *** p$<$.01

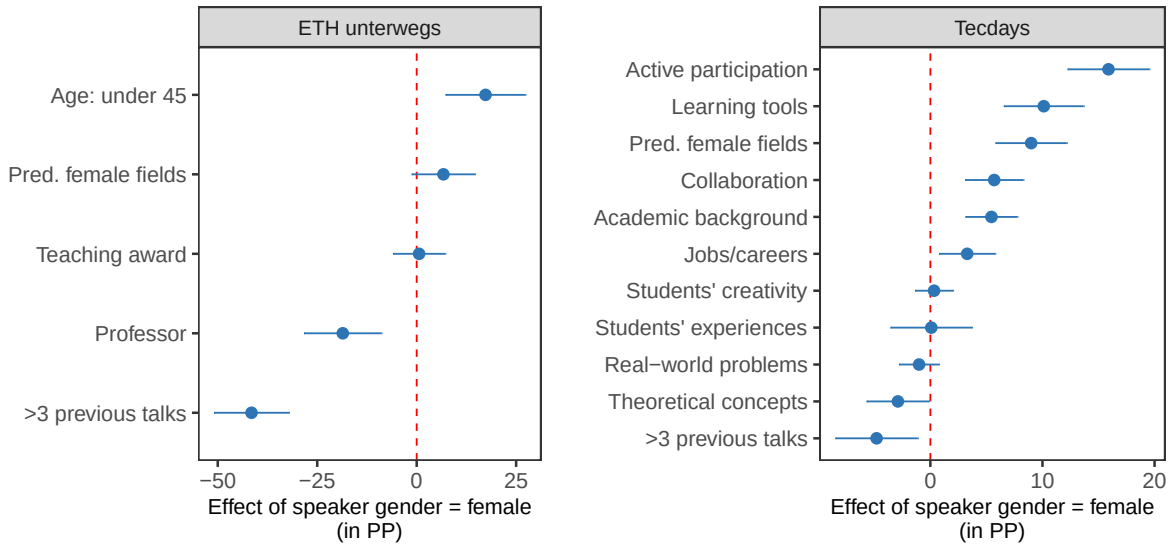


Figure 4: Differences in Speaker and Presentation Characteristics by Speaker Gender

Notes: This figure presents point estimates and standard errors from bivariate regressions of various speaker and presentation characteristics on a dummy for female speakers. The analysis includes 4,965 presentations from 107 *ETH unterwegs* and 76 *Tecdays* events held between 2006 and 2020. Data on presentation field and speaker experience are available for both interventions. Variables on speaker attributes such as speaker age, teaching award status, and professor title apply only to speakers at *ETH unterwegs* events, while data on presentation characteristics is specific to *Tecdays* events and based on presentation descriptions.

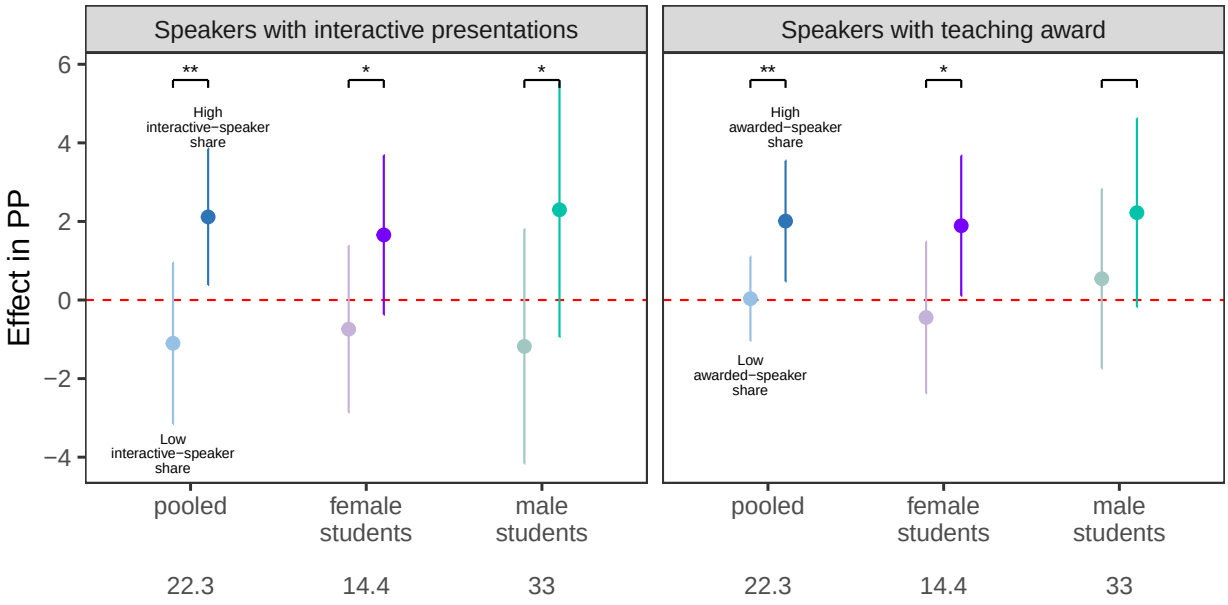


Figure 5: Impact of Event-Level Variation in Speaker Characteristics beyond Speaker Gender on STEM Enrollment

Notes: The figure presents the results for the analysis of changes in speaker composition based on equation (2), exploiting 76 STEM promotions events organized by *Tecdays* (left) and 107 STEM promotion events organized by *ETH unterwegs* (right) between 2006 and 2019. The figure shows the effect of an event, depending on its share of speakers with interactive presentations (left) and who have received a teaching award (right) on the likelihood that a student enrolls in STEM in college. The figure shows the effect of an event on the students who attend an event and graduate in the same year. OLS coefficients with the 95% confidence interval (vertical lines) based on standard errors clustered at the school level are displayed. Significance levels of differences: * p<.1, ** p<.05, *** p<.01

Tables

Table I: Summary Statistics

Variable		
Panel A. Presentation-level data		
	ETH unterwegs	**Tecdays**
N presentations	950	4,015
Speaker characteristics		
Female speaker	11.9 (32.4)	22.7 (41.9)
Prior talks (n)	9.2 (11.3)	5.6 (7.0)
Age (years)	45.2 (12.2)	
Teaching award	12.7 (33.4)	
Professor title	54.4 (49.8)	
Academic employer		11.1 (31.4)
Presentation characteristics		
Topic: female/balanced STEM	20.6 (40.5)	24.8 (43.2)
Students' experiences		59.2 (49.1)
Students' active participation		44.7 (49.7)
Supportive learning tools		37.2 (48.3)
Students' creativity		5.6 (23.0)
Real-world problems		93.9 (24.0)
Students' collaboration		14.6 (35.3)
Career references		13.4 (34.1)
Theoretical concepts		17.1 (37.7)
Panel B. Administrative education data		
	Female HS graduates	**Male HS graduates**
N graduates	137,718	101,581
HS specialization track		
Biology and chemistry	18.3 (38.7)	21.9 (41.4)
Physics and mathematics	4.4 (20.6)	21.0 (40.7)
Non-STEM tracks	77.2 (41.9)	57.1 (49.5)
Enrollment within 2yrs		
...at university	80.9 (39.3)	81.8 (38.6)
...in STEM	14.4 (35.2)	33.0 (47.0)
...in female/balanced STEM	10.0 (30.0)	10.3 (30.4)
...in male STEM	4.7 (21.2)	23.1 (42.1)
STEM bachelor degree within 6yrs	8.8 (28.3)	21.8 (41.3)

Notes: This table summarizes the two main data sources used in the analysis. Panel A reports presentation-level statistics for the two STEM promotion interventions. Panel B reports linked administrative data for high-school (HS) graduates from schools with at least one event. Unless otherwise noted, entries report sample means on a 0–100 scale (i.e., in percent), with standard deviations in parentheses.

Table II: School-Level Activities Correlated with *Tecday/ETH unterwegs* Events

	Annual school calendar mentions any ...					
Outcome	(1) Tecday / ETH unt.	(2) STEM pre-sentation	(3) Other STEM event	(4) STEM study week	(5) Career event	(6) Study event
$Event^{(0)}$	0.898***	-0.068	-0.059	-0.02	0.085	0.041
	(0.061)	(0.069)	(0.077)	(0.063)	(0.078)	(0.07)
School FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Mean	0.2	0.3	0.3	0.3	0.4	0.6
N	244	244	244	244	244	244

Notes: The table shows the point estimates of regressions similar to the static TWFE analysis based on equation (2). All models control for school and graduation-year fixed effects. The regressions are based on school calendars digitized from 244 annual reports from 26 schools that host at least 1 *Tecday* or *ETH unterwegs* event (see Figure A4 for an example). $Event^{(0)}$ takes a value of 1 in the year of any *Tecday/ETH unterwegs* event and 0 otherwise. Model (1) measures whether any *Tecday/ETH unterwegs* event is mentioned. (2) - (4) indicate whether any other STEM activities are mentioned. (5) and (6) show whether any career or study information event is mentioned. Standard errors adjusted for clustering on the school level are displayed.* p<.1, ** p<.05, *** p<.01

Table III: Impact of STEM Events on the Probability of Enrolling and Obtaining a Degree in STEM in College

Dependent Variables, in college:	**STEM enrollment**		**STEM bachelor degree**	
	(1)	**(2)**	**(3)**	**(4)**
$Event^{(0)}$	0.954**		1.109**	
	(0.381)		(0.453)	
$Event^{(-20,-2)}$	0.395		0.35	
	(0.389)		(0.401)	
$Event^{(1,13)}$	0.262		0.589	
	(0.411)		(0.465)	
$Event^{(0)}$		0.716		0.856*
		(0.51)		(0.498)
Gender: Male $\times$ $Event^{(0)}$		0.519		0.616
		(0.916)		(0.71)
$Event^{(-20,-2)}$		0.077		0.122
		(0.368)		(0.364)
Gender: Male $\times$ $Event^{(-20,-2)}$		0.171		0.103
		(0.676)		(0.626)
$Event^{(1,13)}$		0.184		0.409
		(0.416)		(0.431)
Gender: Male $\times$ $Event^{(1,13)}$		0.057		0.165
		(0.794)		(0.724)
School FE	Y	Y	Y	Y
Graduation Year FE	Y	Y	Y	Y
Mean	22.3	22.3	14.4	14.4
N students	239,299	239,299	192,553	192,553

Notes: The table shows the point estimates of the static TWFE analysis based on equation (2). The main parameter of interest is $Event^0$, which takes a value of 1 for students who attend an event and graduate in the same year and 0 otherwise. $Event^{(-20,-2)}$ and $Event_{st}^{(1,13)}$ account for all events for students graduating two or more years before an event and one or more years after an event. The omitted comparison period consists of the students who graduate in the academic year immediately before an event. All models include school and graduation-year fixed effects. Model (1) represents my baseline specification and shows the effect of the events on the likelihood of enrolling in STEM within 2 years (sample: graduating cohorts 1999/00-2019/20). (3) shows the effect of the events on the likelihood of obtaining an undergraduate degree in STEM in college in the 6 years after high school graduation (sample: graduating cohorts 1999/00-2015/16). (2) and (4) interact all event dummies and fixed effects with a dummy for male student gender. Standard errors adjusted for clustering on the school level are displayed.* p<.1, ** p<.05, *** p<.01

Table IV: Robustness of Results to Alternative Specifications

	Dependent Variable: STEM enrollment in college						
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Event^{(0)}$	0.954**	0.914***	1.032***	1.145***	0.964**	0.953**	0.790***
	(0.381)	(0.345)	(0.376)	(0.395)	(0.404)	(0.387)	(0.264)
$Event^{(-20,-2)}$	0.395	0.344	0.393	0.082	0.333		0.228
	(0.389)	(0.406)	(0.362)	(0.314)	(0.349)		(0.30)
$Event^{(1,13)}$	0.262	0.799	0.492	0.281	0.417		
	(0.411)	(0.493)	(0.396)	(0.371)	(0.457)		
$Event^{(5,13)}$							0.095
							(0.399)
Specification	Baseline	Equal weights	All schools	Stacked, clean controls	School trends	Simple DiD	Treated control
School FE	Y	Y	Y	Y	Y	Y	Y
Grad. Yr. FE	Y	Y	Y	Y	Y	Y	Y
Mean	22.3	22.3	21.4	20.9	22.3	20.9	22.3
N students	239,299	239,299	353,418	265,137	239,299	166,275	239,299

Notes: The table shows the point estimates of the static TWFE analysis based on equation (2). The main parameter of interest is $Event^0$, which takes a value of 1 for students who attend an event and graduate in the same year and 0 otherwise. $Event^{(-20,-2)}$ and $Event_{st}^{(1,13)}$ account for all events for students graduating two or more years before an event and one or more years after an event. The omitted comparison period consists of the students who graduate in the academic year immediately before an event. All models include school and graduation-year fixed effects. (1) represents my baseline specification. (2) combines the estimates for each school with equal weights following the estimation procedure by Sun and Abraham (2021). (3) includes all 142 schools. (4) implements a stacked event study similar to Cengiz et al. (2019), where each event receives a separate stack and only untreated schools serve as control schools. (5) includes linear school-specific trends to the baseline. (6) shows a simple DID specification in which from treated schools only the students who graduate just before and after an event are included. (7) allocates students who attend an event and graduate in the years after an event to the control group. Standard errors adjusted for clustering on the school level are displayed.* p<.1, ** p<.05, *** p<.01

Table V: Impact of Increasing the Share of Female Speakers on the Probability of Enrolling in STEM in College, After Controlling for Presentations Characteristics

	Dependent Variable: STEM enrollment in college			
Model	(1)	(2)	(3)	(4)
Tecdays$^{(0)}$	-1.007	-1.647	-1.197	-2.127
	(1.014)	(1.173)	(2.805)	(2.826)
Tecdays, high female-speaker share$^{(0)}$	2.725*	1.738	1.345	3.382*
	(1.417)	(1.222)	(1.426)	(1.912)
Tecdays, high interactive-pres. share$^{(0)}$		2.525**	2.781*	5.474***
		(1.154)	(1.459)	(2.039)
High female-speaker share$^{(0)}$ x *High interactive-pres. share*$^{(0)}$				-4.465**
				(2.2)
School FE	Y	Y	Y	Y
Graduation Year FE	Y	Y	Y	Y
All presentation traits[1]			Y	Y
Mean	22.3	22.3	22.3	22.3
N students	239,299	239,299	239,299	239,299

[1] Controls: creativity, experiences, careers, real-world problems, theoretical concepts, topic, speaker experience, academic background

Notes: The table shows point estimates based on regressions similar to equation (2). All models control for school and graduation-year fixed effects and include controls for *ETH unterwegs* events, plus binned leads and lags for all event types (*ETH unterwegs*, *Tecdays*, *Tecdays, high female-speaker share*, *Tecdays, high interactive-presentation share*), which are for clarity not displayed in the table. Standard errors adjusted for clustering on the school level are displayed.* p<.1, ** p<.05, *** p<.01

Appendix

A Text Classification

In this appendix, I describe in detail how I use the ChatGPT API to classify presentation descriptions based on content and style.

The classification dimensions are derived from a manual provided by the Swiss Academy of Engineering Sciences, which gives prospective speakers recommendations for delivering engaging and inspiring presentations to high school students. The manual suggests: (i) topics relevant to students' experiences, (ii) interactivity and dialogue with students, (iii) the use of supportive presentation tools or materials, and (iv) explanations of one's profession and career path.

For each dimension, I design a unique prompt. Below is the exact prompt used to classify whether a presentation involves *students' active participation*:

> You are an objective observer designed to classify short summaries of presentations delivered by STEM professionals to high school students. Would an objective observer agree with the statement that this presentation involves students' active participation during the presentation? First, provide an explanation (max 60 tokens). Then pick exactly 1 answer from the following 2 answers delimited by triple dashes below: —Yes, the observer would agree.— —No, the observer would not agree.— Don't pick an answer until you have provided the explanation and answered the question for yourself.

The prompts for other dimensions follow a similar structure but ask different questions based on each classification category. The specific questions for each dimension are as follows:

- *Students' experiences*: Would an objective observer agree with the statement that this presentation speaks of issues or phenomena that have been experienced by the students or people in their community?
- *Presentation tools*: Would an objective observer agree with the statement that this presentation uses presentation tools, such as samples, exhibits, videos, audio, software, devices or models, for the purpose of the presentation?
- *Students' creativity*: Would an objective observer agree with the statement that this presentation explicitly refers to students' creativity?
- *Real-world problems*: Would an objective observer agree with the statement that this presentation exposes students to current real-world problems?
- *Collaboration*: Would an objective observer agree with the statement that this presentation mentions collaborating or working together as a team?
- *Jobs/careers*: Would an objective observer agree with the statement that this presentation mentions specific occupations or careers?

- *Theoretical concepts*: Would an objective observer agree with the statement that this presentation teaches theoretical models or concepts?

I use the ChatGPT version known as GPT-4o-mini, the latest version available as of writing this study. I follow several techniques recommended by Openai, the company developing ChatGPT, on prompt engineering to optimize the results and enhance reliability. First, I ask the model to adopt a persona. Second, I ask for a justification. Third, I give the model time to 'think' by requiring ChatGPT to answer the question first before picking an answer. Finally, I clearly demarcate the answer options from other instructions. These techniques have been shown to restrict hallucinations and to improve its accuracy.

To assess the accuracy of this classification procedure, I cross-check ChatGPT's categorization with manual coding of presentation descriptions for a subsample of 960 presentations from a randomly selected set of nine events. I focus on two dimensions: *students' active participation* and *presentation tools*. For active participation, I identify descriptions that mention participation indicators, such as 'asking questions', 'discussions', 'quizzes.' For presentation tools, I look for descriptions that specify supportive tools, such as 'film', 'audio', 'experiments', or 'exhibits.'

I evaluate ChatGPT's performance on these dimensions using two commonly applied parameters in text classification: precision and recall. Precision measures the proportion of items correctly assigned to a condition out of all items assigned that condition, while recall measures the proportion of items correctly assigned to a condition out of all items that should be assigned that condition. The following describes these two parameters formally:

$$precision = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

$$recall = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

Higher precision indicates fewer false positives, and higher recall indicates fewer false negatives. Compared to the hand-coded subsample, ChatGPT achieves 91.4% precision and 85.8% recall for *students' active participation* and 91.7% precision and 71.1% recall for *presentation tools*. Thus, 8.6% of presentations identified by ChatGPT as involving active participation may not actually include it (false positives), and approximately one in seven presentations involving active participation may be missed (false negatives).

B Appendix Figures



Figure A1: Flyer for *ETH unterwegs*

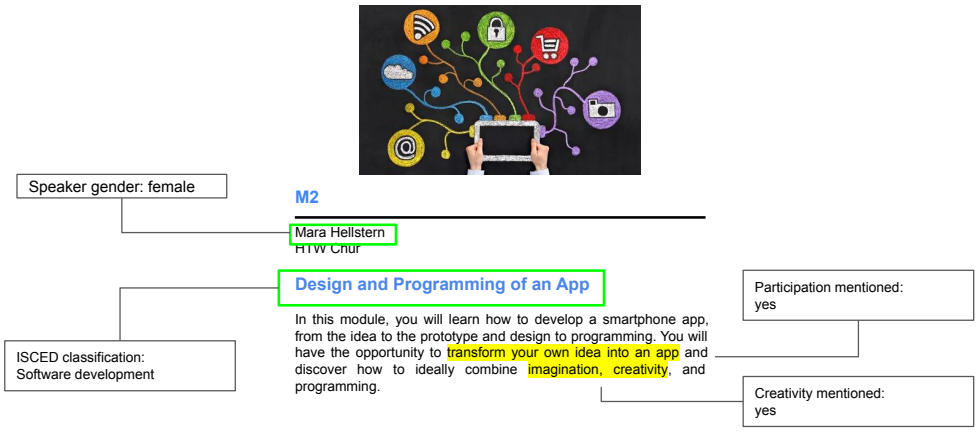


Figure A2: Presentation Description on *Tecdays* flyer

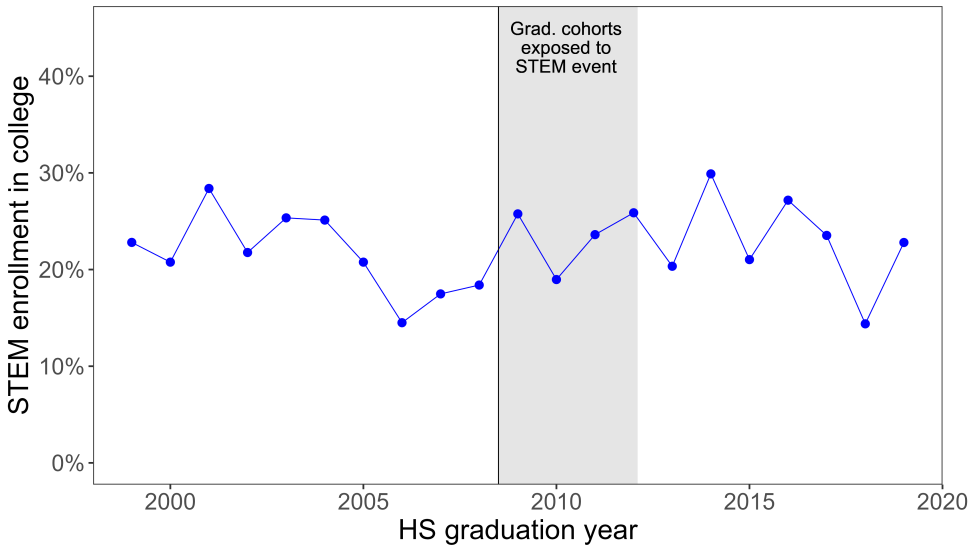


Figure A3: Example: STEM Enrollment in College at a Selected School

Notes: The figure plots the raw likelihood to enroll in STEM in college within 2 years from graduating from high school for students from a single school. The black vertical line indicates that an event takes place at the school during the school year 2009/2010.

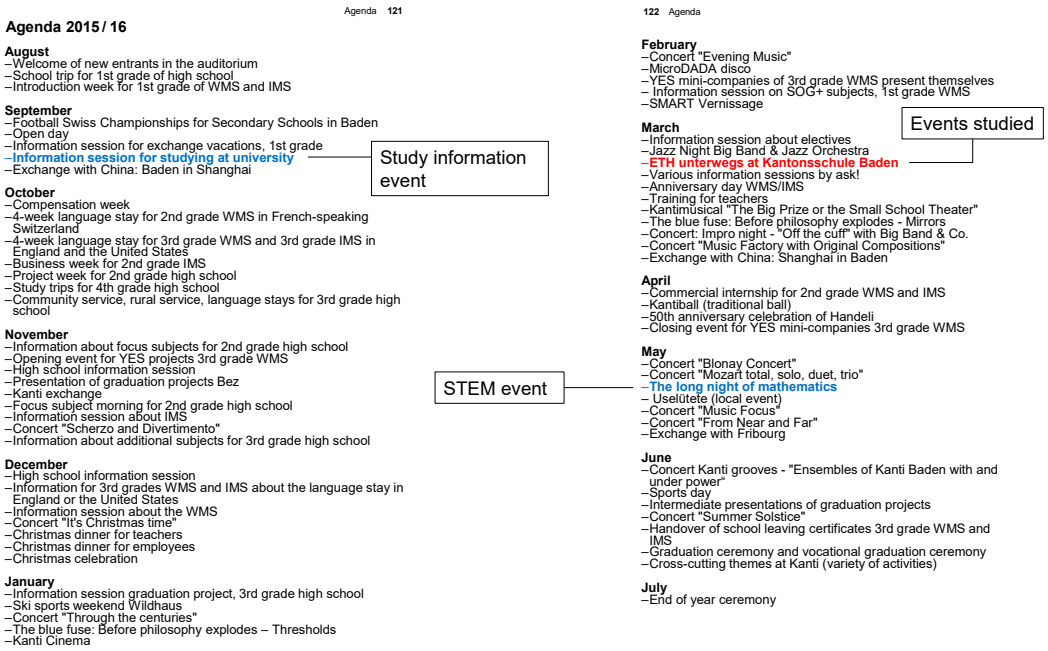


Figure A4: Example: School Calendar

Notes: The figure shows an example of the 244 school calendars used to analyze whether schools are more likely to organize other STEM or career activities in years they host a *Tecday / ETH unterwegs* event. Entries for potentially other relevant activities are highlighted in blue.

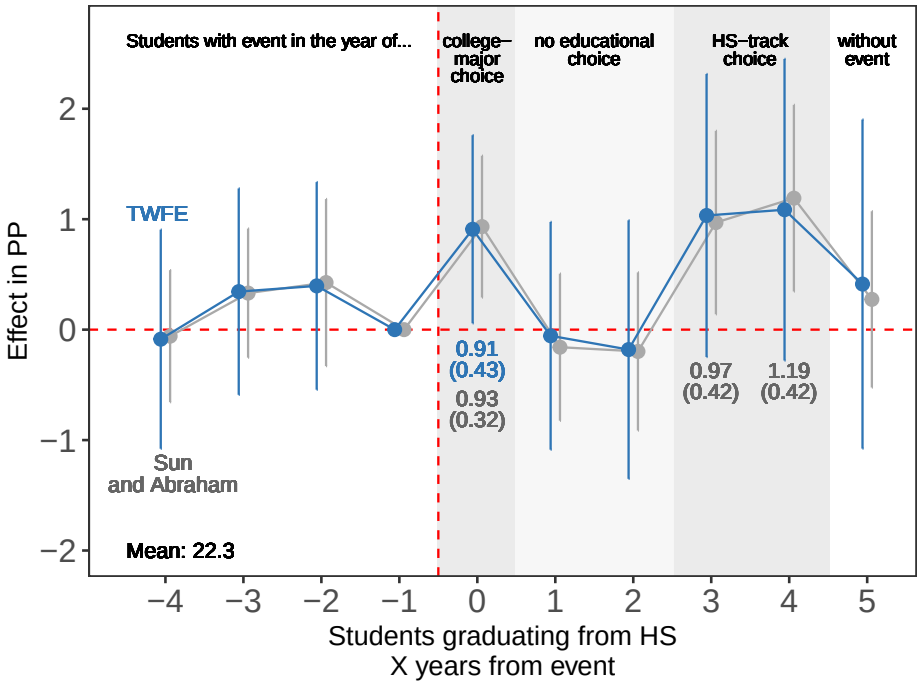


Figure A5: Impact of STEM Events on the Probability of Enrolling in STEM in College

Notes: The figure shows the results from the event study TWFE analysis (blue) as in equation (1), Sun and Abraham (2021) (grey) follows the estimation procedure proposed by the authors and combines the estimates for each school with equal weights. Exploiting 183 STEM promotion events between 2006 and 2019, the figure shows the effect of an event on the likelihood that a student enrolls in STEM in college within 2 years after graduating from high school. OLS coefficients with the 95% confidence interval (vertical lines) based on standard errors clustered at the school level are displayed.

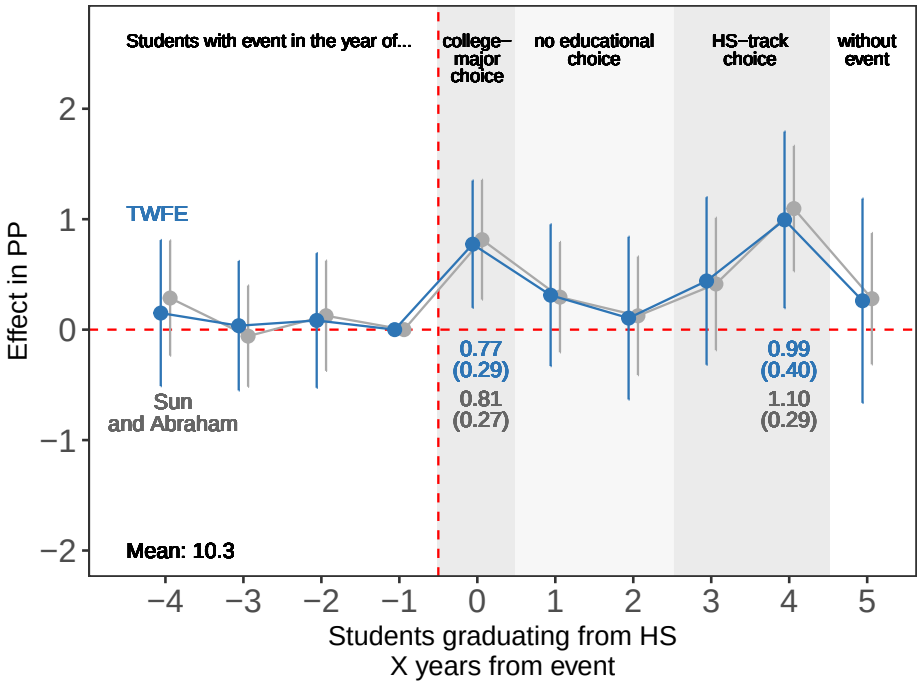


Figure A6: Impact of STEM Events on the Probability of Enrolling in STEM at ETH Zurich

Notes: The figure shows the results from the event study TWFE analysis (blue) as in equation (1), Sun and Abraham (2021) (grey) follows the estimation procedure proposed by the authors and combines the estimates for each school with equal weights. Exploiting 183 STEM promotion events between 2006 and 2019, the figure shows the effect of an event on the likelihood that a student enrolls in STEM at ETH Zurich within 2 years after graduating from high school. OLS coefficients with the 95% confidence interval (vertical lines) based on standard errors clustered at the school level are displayed.

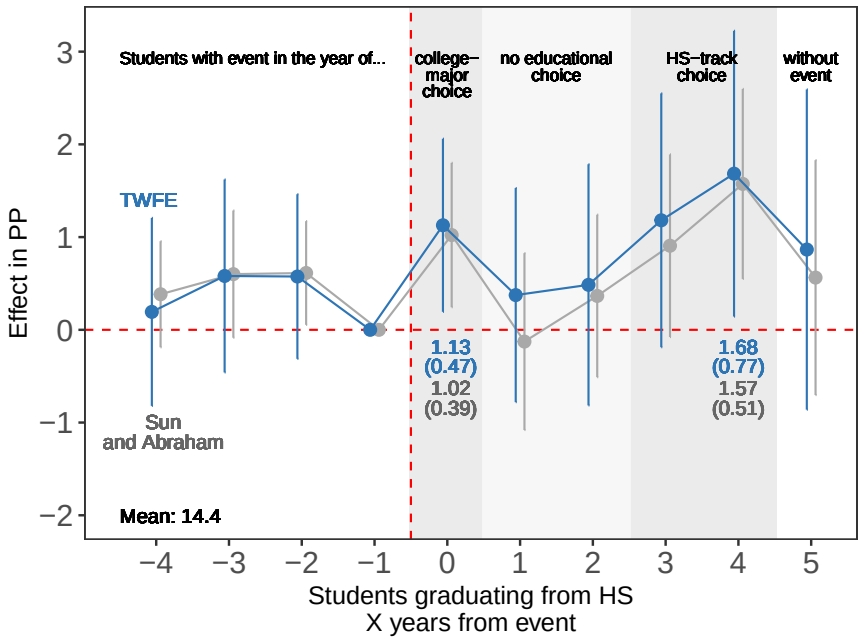


Figure A7: Impact of STEM Events on the Probability of Obtaining a STEM Degree in College

Notes: The figure shows the results from the event study TWFE analysis (blue) as in equation (1), Sun and Abraham (2021) (grey) follows the estimation procedure proposed by the authors and combines the estimates for each school with equal weights. Exploiting 124 STEM promotion events between 2006 and 2015, the figure shows the effect of an event on the likelihood that a student obtains a STEM degree in college within 6 years after graduating from high school. OLS coefficients with the 95% confidence interval (vertical lines) based on standard errors clustered at the school level are displayed.

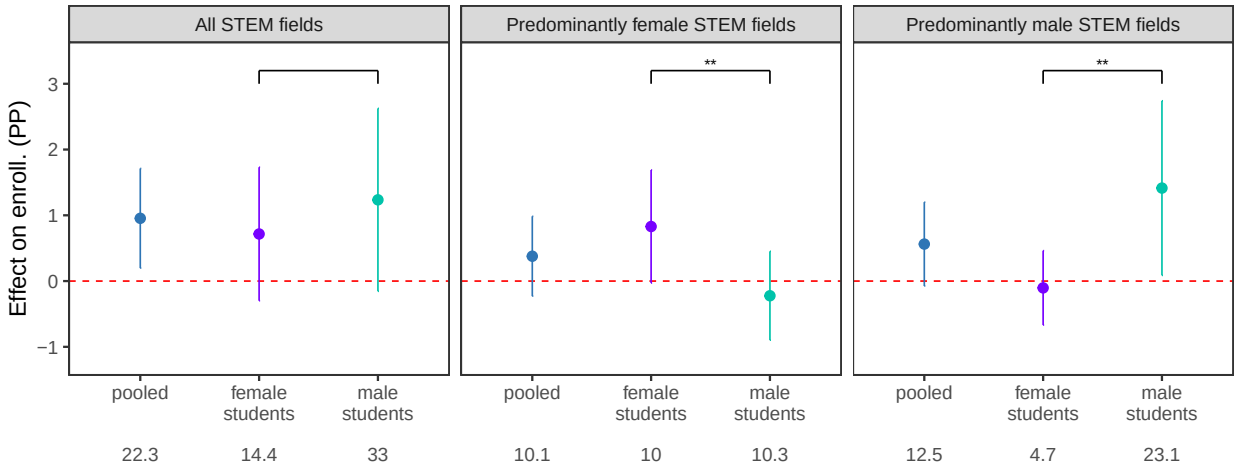
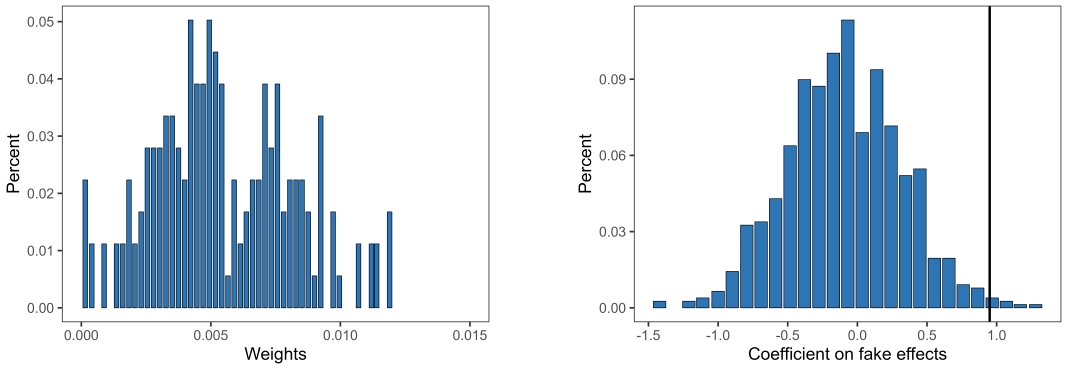


Figure A8: Gender Differences in Event Impact

Notes: The figure shows the results from the static TWFE analysis as in equation (2), exploiting 183 STEM promotion events between 2006 and 2019. The figure shows the effect of an event on the likelihood that a student enrolls in STEM in college after graduating from high school for the students who attend an event and graduate in the same year. STEM is separated into predominantly female or gender-balanced (female share $> 40\%$) and predominantly male fields. OLS coefficients with the 95% confidence interval (vertical lines) based on standard errors clustered at the school level are displayed. Significance levels of differences: * p<.1, ** p<.05, *** p<.01



(a) Distribution of Weights

(b) Permutation Interference

Figure A9: Assessing Biases in the TWFE Estimator

Notes: (a) shows the distribution of the weights associated with the TWFE estimator, following De Chaisemartin and d'Haultfoeuille (2020). (b) shows the distribution of effects when I reallocate the 183 events randomly across schools and years over 1,000 replications. The vertical bar indicates the coefficient obtained from the actual distribution of events.

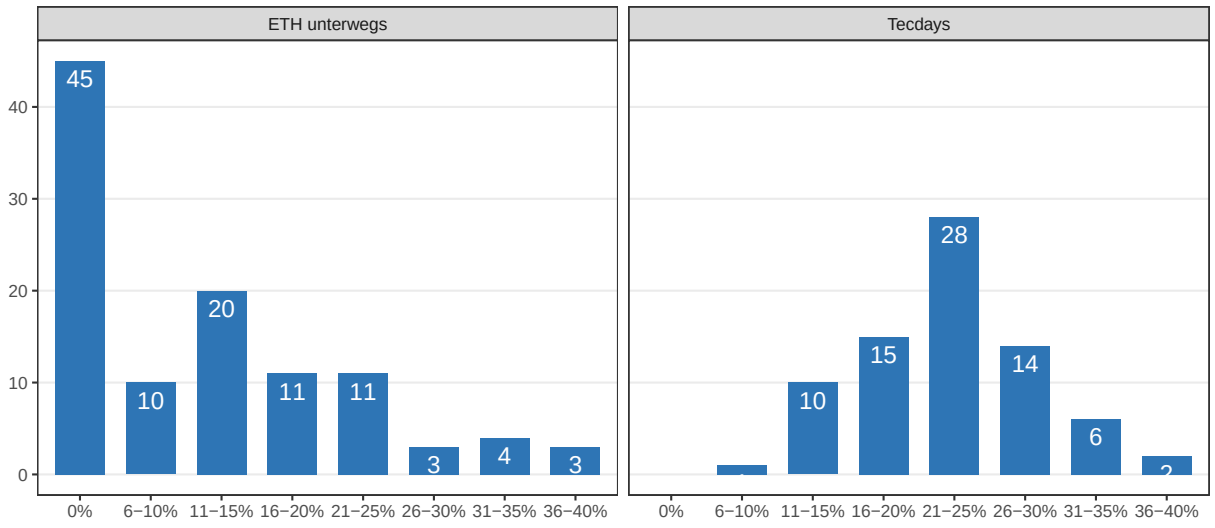


Figure A10: Distribution of Events by Share of Female Speakers

Notes: The figure shows the number of events by share of female speakers. The total number of events is 183. *ETH unterwegs* events with a high share of female speakers comprise all events with a female-speaker share larger than 9.1%, *Tecdays* with a high share of female speakers comprise events with a share of female speakers larger than 22.4%.

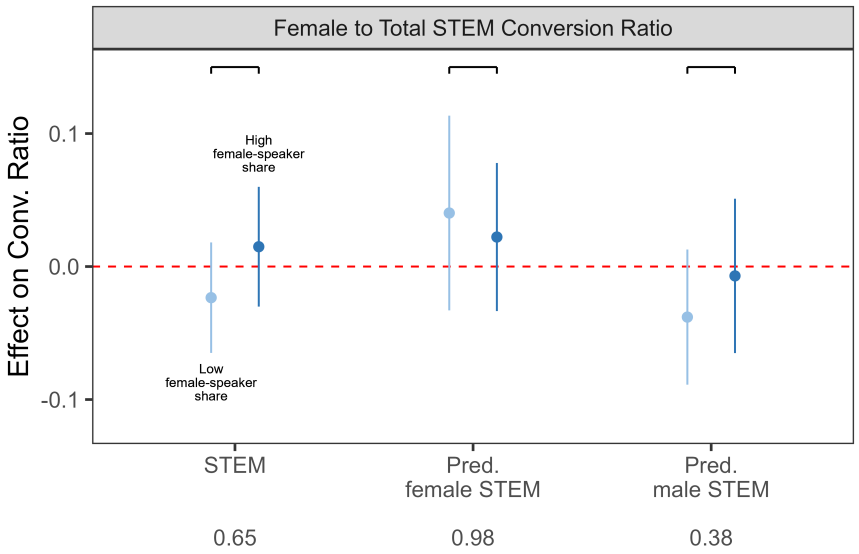


Figure A11: Impact of Event-Level Variation in Female-Speaker Share on the Female to Total STEM Conversion Rate

Notes: The figure presents the results for the analysis of changes in speaker composition based on equation (2), exploiting 183 STEM promotion events between 2006 and 2019. The figure shows the effect of an event, depending on its share of female speakers, on the female to total STEM conversion rate. The conversion rate is calculated as follows: (female HS graduates enrolled in STEM in college / female HS graduates) / (total HS graduates enrolled in STEM in college / total HS graduates). This ratio is similar to the one employed by Avilova and Goldin (2024). If the intervention increases STEM enrollment more strongly for female than male students, the conversion ratio will increase. The effect of an event on the students who attend an event and graduate from high school in the same year is shown. OLS coefficients with the 95% confidence interval (vertical lines) based on standard errors clustered at the school level are displayed. Significance levels of differences: * p<.1, ** p<.05, *** p<.01

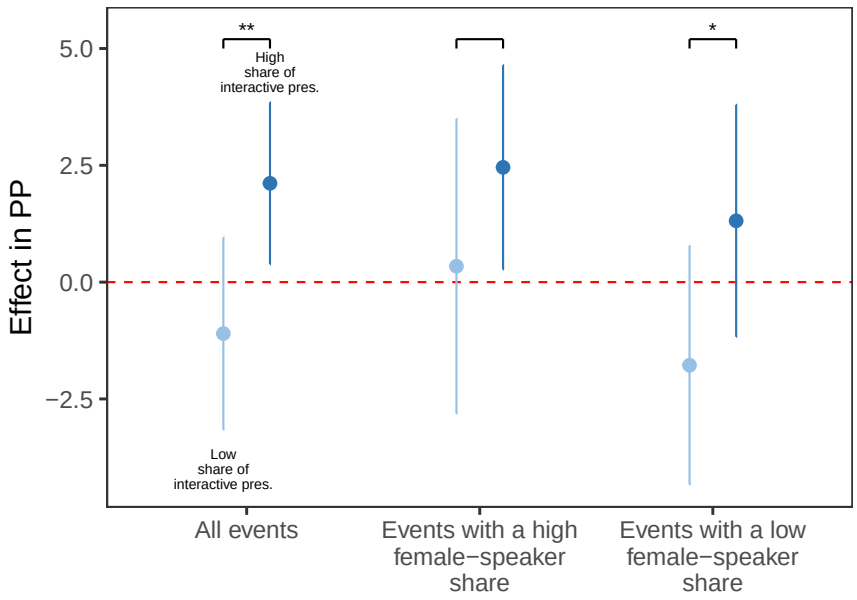


Figure A12: Impact of Event-Level Variation in the Share of Interactive Presentations on STEM Enrollment, by Female-Speaker Share

Notes: The figure presents the results for the analysis of changes in speaker composition based on equation (2), exploiting 183 STEM promotion events between 2006 and 2019. The figure shows the effect of an event, depending on its share of interactive presentations, on the likelihood that a student enrolls in STEM in college after graduating from high school. The effect of an event on the students who attend an event and graduate from high school in the same year is shown. Interactive presentations are defined as those incorporating active participation, student collaboration, or presentation tools. OLS coefficients with the 95% confidence interval (vertical lines) based on standard errors clustered at the school level are displayed. Significance levels of differences: * p<.1, ** p<.05, *** p<.01

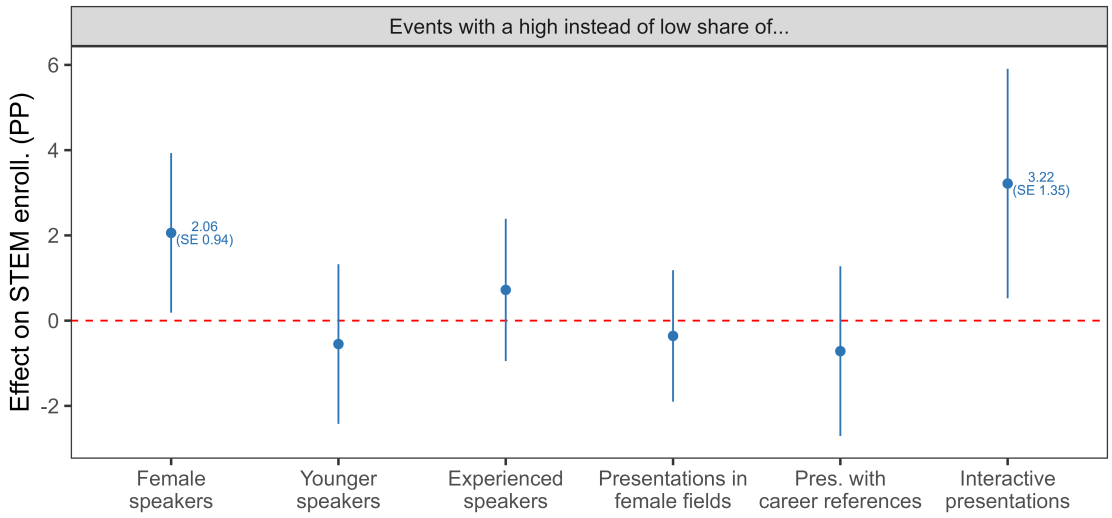


Figure A13: Impact of Gender-Correlated Speaker and Presentation Characteristics on STEM Enrollment in College

Notes: This figure illustrates the estimated impact of event-level variation in speaker and presentation characteristics on students' likelihood of enrolling in STEM fields in college, based on Equation (2). The analysis covers 183 STEM promotion events organized between 2006 and 2019. Effects from separate regressions comparing events with a high share versus low share of speakers or presentations featuring specific characteristics, on students who attended and graduated high school the same year, are displayed. Interactive presentations are defined as those incorporating active participation, student collaboration, or presentation tools. The figure presents OLS coefficients with 95% confidence intervals (indicated by vertical lines), with standard errors clustered at the school level.

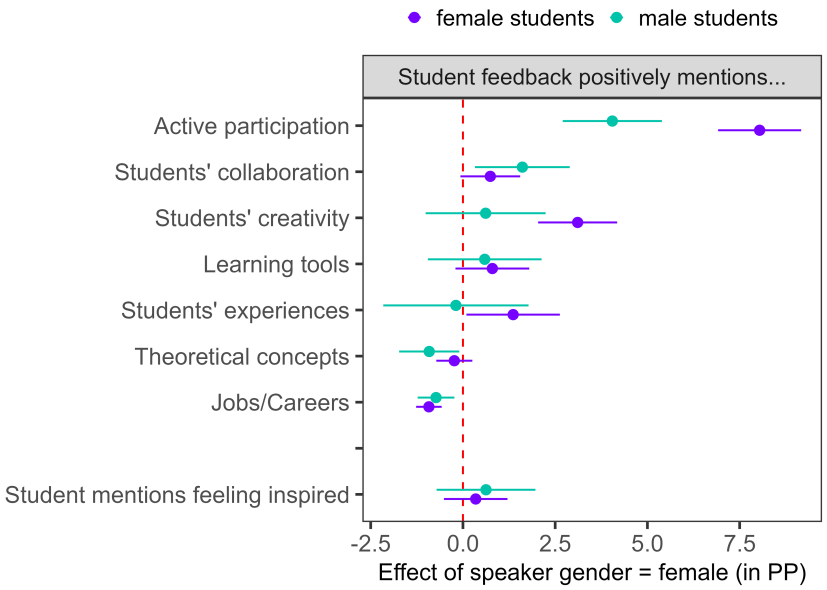


Figure A14: Presentation Characteristics More Frequently Cited in Student Feedback for Female vs. Male Speakers

Notes: This figure displays OLS coefficients from bivariate regressions examining whether specific presentation characteristics are mentioned more frequently in feedback for female than for male speakers. The analysis draws on 29,775 responses from 9,484 students across 38 post-event surveys following *Tecdays* events. Students responded to an open-ended question on what particularly impressed them about each presentation they attended. Responses were classified using ChatGPT, as detailed in Section 3. OLS coefficients with the 95% confidence interval (vertical lines) are displayed.

C Appendix Tables

Table A1: STEM Study Fields by Gender Mix

Gender mix	STEM field
Predominantly male	Mechanical Engineering, Electrical Engineering, Microtechnology, Computer Science, Communication Systems, Management and Manufacturing Sciences, Interdisciplinary Exact Sciences, Physics, Civil Engineering, Chemical Engineering, Astrology, Materials Science, Chemistry, Rural Engineering and Surveying, Mathematics, Earth Sciences
Predominantly female / gender-balanced	Geography, Architecture and Planning, Interdisciplinary Natural Sciences, Interdisciplinary Exact Sciences and Natural Sciences, Biology, Interdisciplinary Engineering, Food Science

Notes: The table shows all STEM study fields, separated by students' gender mix in college. STEM study fields belong to the following fields as classified by the International Standard Classification of Education (ISCED) classification system (UNESCO, 2015): natural sciences, mathematics, and statistics (ISCED-05), information and communication technologies (ISCED-06), and engineering, manufacturing, and construction (ISCED-07). Fields are separated into predominantly female or gender-balanced (female share $> 40\%$) and predominantly male fields (female share $< 40\%$).

Table A2: Data Structure and Parameters for School with 2 Events

i	t	$E_{st}^{(-20,-5)}$	$E_{st}^{(-4)}$	$E_{st}^{(-3)}$	$E_{st}^{(-2)}$	$E_{st}^{(-1)}$	$E_{st}^{(0)}$	$E_{st}^{(1)}$	$E_{st}^{(2)}$	$E_{st}^{(3)}$	$E_{st}^{(4)}$	$E_{st}^{(5)}$	$E_{st}^{(6,13)}$
a	2005	2	0	0	0	0	0	0	0	0	0	0	0
b	2006	2	0	0	0	0	0	0	0	0	0	0	0
c	2007	1	1	0	0	0	0	0	0	0	0	0	0
d	2008	1	0	1	0	0	0	0	0	0	0	0	0
e	2009	0	1	0	1	0	0	0	0	0	0	0	0
f	2010	0	0	1	0	1	0	0	0	0	0	0	0
g	2011	0	0	0	1	0	1	0	0	0	0	0	0
h	2012	0	0	0	0	1	0	1	0	0	0	0	0
i	2013	0	0	0	0	0	1	0	1	0	0	0	0
j	2014	0	0	0	0	0	0	1	0	1	0	0	0
k	2015	0	0	0	0	0	0	0	1	0	1	0	0
l	2016	0	0	0	0	0	0	0	0	1	0	1	0
m	2017	0	0	0	0	0	0	0	0	0	1	0	1
n	2018	0	0	0	0	0	0	0	0	0	0	1	1
o	2019	0	0	0	0	0	0	0	0	0	0	0	2

Notes: The table illustrates the data structure and the coding of the parameters described in equation (1). I assume a school s with 1 student i graduating each year t. Students graduate between $t = 2005$ to $t = 2019$. For school s, the first event takes place in 2011 and the second in 2013. For brevity, I shorten *Event* to E.

Table A3: Joint associations between coded presentation characteristics and student feedback

	Feedback mentions...						
Pres. descr. mentions...	Active partic.	Collabor.	Learning tools	Creativity	Students' exper.	Career	Theory
Active partic.	**0.08*** **	0.01	0.00	0.01	0.01	-0.01***	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Collaboration	0.04***	**0.02** **	-0.02**	-0.00	-0.01	0.00	-0.00
	(0.01)	**(0.01)**	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Learn. tools	0.04***	-0.00	**0.02*** **	0.01	0.01	-0.01***	0.01
	(0.01)	(0.01)	**(0.01)**	(0.01)	(0.01)	(0.00)	(0.00)
Creativity	0.05***	0.03***	-0.01	**0.14*** **	0.00	-0.01**	-0.00
	(0.01)	(0.01)	(0.01)	**(0.02)**	(0.01)	(0.00)	(0.01)
Students' exper.	-0.01*	0.00	0.01	-0.02**	**0.03*** **	-0.02***	-0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	**(0.01)**	(0.00)	(0.00)
Careers	0.02	-0.01	-0.00	-0.01	-0.03**	**0.01** **	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	**(0.00)**	(0.01)
Theory	-0.01	-0.01	-0.02***	0.01	0.00	-0.01***	**0.01** **
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	**(0.00)**

Notes: The analysis draws 29,775 responses from 9,484 students across 38 post-event surveys to 1,595 presentations following *Tecdays* events. Students responded to an open-ended question on what particularly impressed them about each presentation they attended. Presentation descriptions and feedback responses were classified using ChatGPT, as detailed in Section 3. Each column corresponds to a separate regression of the indicated feedback outcome on all coded presentation characteristics simultaneously, including student fixed effects. Standard errors clustered at the student level are in parentheses. Bold entries indicate the matched characteristic-feedback pair. p<.1, ** p<.05, *** p<.01

Table A4: Impact of STEM Events on the Probability of Enrolling in a STEM in College by Timing of High School Track Choice

	Dependent Variable: STEM enrollment in college	
	(1)	**(2)**
HS track choice	Upon HS entry	During high school
$Event^{(0)}$	0.596	1.1
	(0.416)	(0.725)
$Event^{(1,2)}$	-0.476	0.248
	(0.572)	(0.912)
$Event^{(3,4)}$	0.503	1.97**
	(0.812)	(0.869)
$Event^{(-20,-2)}$	0.276	0.713
	(0.556)	(0.574)
$Event^{(5,13)}$	0.732	0.877
	(0.966)	(0.83)
Mean	21.8	23.1
N students	146,906	92,393

Notes: The table shows the point estimates similar to the static TWFE analysis described in equation (2). The main parameter of interest is $Event^{3,4}$, which takes a value of 1 for students who attend an event in the first years of high school. $Event^{(-20,-2)}$ and $Event_{st}^{(5,13)}$ account for all future and past events for students graduating two or more years before an event and five or more years after an event. The omitted comparison period consists of the students who graduate in the academic year immediately before an event. All models include school and graduation-year fixed effects. Model (1) shows the results for students at schools where HS track choice takes place upon entry to the school. Model (2) comprises schools where students select their HS track in the first two years of high school. Standard errors adjusted for clustering on the school level are displayed.* p<.1, ** p<.05, *** p<.01

Table A5: Impact of STEM Events on the Probability of Enrolling in a STEM Track in High School

	Track choice in high school			
Outcome	Any STEM	Biology & Chemistry	Physics and Mathematics	STEM in college
$Event^{(0)}$	1.011	0.849	0.162	1.076
	(0.685)	(0.668)	(0.529)	(0.867)
$Event^{(-12,-2)}$	0.457	0.338	0.119	-0.37
	(0.631)	(0.659)	(0.317)	(0.582)
$Event^{(1,12)}$	0.248	-0.003	0.251	0.368
	(0.906)	(0.787)	(0.45)	(0.777)
School FE	Y	Y	Y	Y
Graduation Year FE	Y	Y	Y	Y
Mean	31	19.5	11.5	24.4
N students	57,358	57,358	57,358	57,358

Notes: The table shows the point estimates of a static TWFE analysis similar to equation (2). The estimation sample is based on students graduating from 34 high schools that host at least 1 event and at which track choice takes place during high school. The regressions are based on graduation years 2007/08 - 2019/20, the years for which track choice information is available. Event dummies are defined relative to the year when students choose their track in high school, e.g. $Event^{(0)}$ takes a value of 1 for students who attend an event and choose their high school track in the same year. All models control for school and graduation-year fixed effects. Track choice is observed at high school graduation. Standard errors adjusted for clustering on the school level are displayed.* p<.1, ** p<.05, *** p<.01

Table A6: Impact of STEM Events on the Probability of Enrolling in a Study Field in College

	STEM		**Other Study Fields**				
	at ETH	not at ETH	Bus./Law	Arts/Hum.	Educ.	Social Sc.	Health
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Event^{(0)}$	0.807***	0.236	0.502	0.278	-0.059	-0.342	-0.414*
	(0.294)	(0.362)	(0.435)	(0.264)	(0.344)	(0.278)	(0.244)
$Event^{(-20,-2)}$	0.334	0.087	0.602	0.414	-0.112	0.014	0.124
	(0.242)	(0.321)	(0.374)	(0.253)	(0.311)	(0.306)	(0.259)
$Event^{(1,13)}$	0.449	-0.138	0.613	0.468	0.216	0.489*	-0.185
	(0.289)	(0.354)	(0.437)	(0.293)	(0.321)	(0.281)	(0.225)
School FE	Y	Y	Y	Y	Y	Y	Y
Graduation Year FE	Y	Y	Y	Y	Y	Y	
Mean	10.3	12.2	20.2	9.6	9.5	11.1	9.3
N students	239,299	239,299	239,299	239,299	239,299	239,299	239,299

Notes: The table shows the point estimates of the static TWFE analysis based on equation (2). All models control for school and graduation-year fixed effects. The sample consists of the 83 schools with at least 1 event and graduating cohorts 1999/00-2019/20. (1) and (2) separate STEM into STEM enrollment at ETH and STEM enrollment at all other universities. (3) to (7) look at effects of events on other study fields. Standard errors adjusted for clustering on the school level are displayed.* p<.1, ** p<.05, *** p<.01

Table A7: Impact of STEM Events on the Probability of Enrolling in STEM in College by Specialization in High School

	Dependent Variable: STEM in college		
	(1)	**(2)**	**(3)**
Specialization Track	Biology and Chemistry	Physics and Mathematics	Other Tracks
$Event^{(0)}$	1.016	-0.103	0.773*
	(0.906)	(1.35)	(0.427)
$Event^{(-12,-2)}$	0.382	-0.082	0.288
	(0.776)	(1.072)	(0.385)
$Event^{(1,12)}$	0.038	-0.188	-0.169
	(0.762)	(1.329)	(0.473)
School FE	Y	Y	Y
Graduation Year FE	Y	Y	Y
Mean	25.3	31.8	22
N students	30,331	17,383	105,111

Notes: The table shows the point estimates of the static TWFE analysis based on equation (2). All models control for school and graduation-year fixed effects. The sample consists of the 83 schools with at least 1 event and graduating cohorts 2007/08-2019/20. Results for students graduating from high school in different specialization tracks are shown. Standard errors adjusted for clustering on the school level are displayed.* p<.1, ** p<.05, *** p<.01

Table A8: Balance Table for Female-Speaker Share

	Share of female speakers		
Variable	low	high	coef h
N events	91	92	
Event-level characteristics			
N speakers	25.20	27.79	2.596
Month	6.93	6.70	-0.238
School type and size			
Public school	0.99	0.99	0
N graduates	141.00	154.36	13.366
Share of female graduates	0.59	0.58	-0.005
Specialization tracks			
Any STEM track offered	0.97	0.96	-0.011
% f in STEM track	20.90	21.80	0.895
% m in STEM track	40.07	39.01	-1.065
Language region			
German	0.80	0.76	-0.041
French	0.14	0.16	0.02
Italian	0.05	0.08	0.021
Outcomes in college			
% f enrolling in STEM	15.52	16.76	1.242
% m enrolling in STEM	33.71	34.05	0.341

Notes: The table shows balance statistics for all 183 events when events are separated into events with a low or a high female-speaker share. Time-varying characteristics are measured in the last year before an event. Coef h shows the effect of bivariate regressions on a dummy for events with a high share of female speakers. * p<.1, ** p<.05, *** p<.01

Table A9: Impact of Event-Level Variation in Female-Speaker Share on the Probability of Enrolling and Obtaining a Degree in STEM in College

Dependent Variables, in college:	**STEM enrollment**		**STEM bachelor degree**	
	(1)	**(2)**	**(3)**	**(4)**
Event, high	1.958***		1.636**	
female-speaker share$^{(0)}$	(0.613)		(0.775)	
Event, low	-0.347		0.33	
female-speaker share$^{(0)}$	(0.581)		(0.577)	
Event, high		2.116***		1.955***
female-speaker share$^{(0)}$		(0.709)		(0.732)
Gender: Male $\times$ *Event, high*		-0.176		-0.357
female-speaker share$^{(0)}$		(1.127)		(1.074)
Event, low		-0.859		-0.089
female-speaker share$^{(0)}$		(0.666)		(0.6)
Gender: Male $\times$ *Event, low*		0.969		0.825
female-speaker share$^{(0)}$		(1.218)		(1.079)
School FE	Y	Y	Y	Y
Graduation Year FE	Y	Y	Y	Y
Mean	22.3	22.3	14.4	14.4
N students	239,299	239,299	192,553	192,553

Notes: The table shows the point estimates of regressions based on equation (2). The omitted comparison period consists of the students who graduate in the academic year immediately before an event. The effect of an event on the students who attend an event and graduate from high school in the same year is shown. All models include school and graduation-year fixed effects, plus binned leads and lags for all event types (*Event, low female-speaker share*, *Event, high female-speaker share*), which are for clarity not displayed in the table. Model (1) represents my baseline specification and shows the effect of the events on the likelihood of enrolling in STEM within 2 years (sample: graduating cohorts 1999/00-2019/20). (3) shows the effect of the events on the likelihood of obtaining an undergraduate degree in STEM in college in the 6 years after high school graduation (sample: graduating cohorts 1999/00-2015/16). (2) and (4) interact all event dummies and fixed effects with a dummy for male student gender. Standard errors adjusted for clustering on the school level are displayed.* p<.1, ** p<.05, *** p<.01

Table A10: Robustness to Alternative Measures of Female-Speaker Exposure

Measure:	**Female-speaker share**				**N female speakers**
Model	(1)	(2)	(3)	(4)	(5)
High exposure	1.958***	2.091***	1.697*		1.791***
	(0.613)	(0.747)	(0.937)		(0.583)
Low exposure	-0.347	0.200	-1.081		-0.234
	(0.581)	(0.714)	(1.002)		(0.641)
Linear (1 SD)				1.288**	
				(0.552)	
p-value: High = Low	0.030	0.097	0.054		0.022
Specification	Discrete	ETH unterwegs	Tecdays	Linear	Discrete
Mean	22.3	22.3	22.3	22.3	22.3
N students	239,299	239,299	239,299	239,299	239,299

Notes: The table shows the point estimates of the static TWFE analysis based on equation (2). The effect of an event on the students who attend an event and graduate from high school in the same year is shown. The dependent variable is the likelihood that a student enrolls in STEM in college after graduating from high school. The omitted comparison period is the academic year immediately preceding an event. (1)–(3) use indicators for high and low female-speaker-share exposure. (4) replaces these indicators with a continuous measure of female-speaker share standardized to mean zero and standard deviation one. (5) uses the number of female speakers rather than the share of female speakers. All specifications include school and graduation-year fixed effects, as well as binned leads and lags for all event types. Standard errors adjusted for clustering on the school level are displayed.* $p<.1$, ** $p<.05$, *** $p<.01$

Table A11: Balance Table for Share of Interactive Presentations

	Share of interactive presentations		
Variable	low	high	coef h
N events	39	37	
Event-level characteristics			
N speakers	51.54	54.19	2.651
Month	7.97	7.30	-0.677
School type and size			
Public school	0.95	1.00	0.051
N graduates	148.29	136.97	-11.318
Share of female graduates	0.57	0.59	0.014
Specialization tracks			
Any STEM track offered	0.97	0.97	-0.001
% f in STEM track	23.20	26.98	3.772
% m in STEM track	41.69	45.59	3.901
Language region			
German	0.72	0.68	-0.042
French	0.26	0.19	-0.067
Italian	0.03	0.14	0.109*
Outcomes in college			
% f enrolling in STEM	17.16	17.62	0.463
% m enrolling in STEM	34.00	36.14	2.134

Notes: The table shows balance statistics for all 76 Tecdays when events are separated into events with a low or a high share of interactive presentations. Time-varying characteristics are measured in the last year before an event. Coef h shows the effect of bivariate regressions on a dummy for events with a high share of interactive presentations. * p<.1, ** p<.05, *** p<.01