Does Exposure to Female STEM Professionals Reduce the Gender Gap in STEM Participation?

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December 8, 2024

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Abstract

This study provides large-scale evidence on the impact of brief exposure to STEM professionals on high-school students' STEM participation in college. I link novel data on over 1,500 female and male speakers at 183 STEM promotion events to the educational trajectories of all high-school graduates in Switzerland. Using an event-study design, I find that event exposure increases STEM enrollment in college and leads to higher STEM graduation rates within six years of high-school completion. I then exploit event-level variation in speaker composition to show that events have a stronger impact when the share of female speakers is higher. This effect, however, applies to both female and male students, indicating that female speakers influence students through mechanisms beyond the commonly assumed same-gender role-model effect. Leveraging data extracted from 4,000 presentation descriptions, I find that both female and male students respond positively to interactive presentations, which are more frequent among female speakers.

*ETH Zurich. Email: bamert@kof.ethz.ch. I am grateful to my advisors Michael Siegenthaler and Ulf Zölitz for their guidance throughout the project. I thank Iris Bohnet, Michela Carlana, Raj Chetty, Will Dobbie, Susan Dynarski, Lawrence Katz, Amanda Pallais, Ursina Schaede, Clémentine Van Effenterre, and participants at seminars and conferences at Harvard, Zurich, Cesifo, EALE, and IZA for helpful discussions and feedback. This research is supported by a Research Fellowship at the Women and Public Policy Program at the Harvard Kennedy School.

1 Introduction

How can we increase female students' enrollment in male-dominated fields, such as STEM or economics? Despite the convergence in gender roles, women remain underrepresented in these fields, with negative implications for talent allocation and economic growth (Goldin, 2014; Bertrand, 2020; Hsieh et al., 2019). Drawing on evidence from female political leadership (Beaman et al., 2012), research shows that female teachers increase female students' participation in traditionally male-dominated fields (Card et al., 2022; Carrell et al., 2010). Recent experimental studies find that even brief presentations by female professionals can influence female students' study choices (Breda et al., 2023; Porter and Serra, 2020). Women are often thought to inspire female students as role models in such interactions, with minimal impact on male students. Yet, whether the results generalize at scale remains unclear, particularly given limited evidence on the underlying mechanisms (Bertrand and Duflo, 2017).

Are interventions with female professionals effective at reducing the gender gap in STEM participation? I investigate this question by examining the impact of two large-scale STEM promotion event series in Switzerland: *ETH unterwegs* and *Tecdays*. Between 2006 and 2019, the initiatives exposed over 80,000 high-school students across the country to more than 4,000 presentations by female and male STEM professionals. By linking event data to administrative data covering the entire population of Swiss high-school graduates, I assess the effects of these interventions on high-school students' STEM enrollment and graduation rates in college, following students for up to six years after high-school graduation.

In the first part of the paper, I use an event-study design to estimate the effect of a STEM promotion event occurring in a high school on the likelihood that a student who graduates from the school later enrolls or graduates in a STEM field in college. In the second part, I exploit event-level variation in speaker and presentation composition to disentangle the impact of speaker gender from other factors, such as presentation style or content.

The events aim to increase students' interest in STEM by exposing them to multiple presentations delivered by STEM professionals over the course of a single school day. Two event features are particularly relevant to my analysis. First, the events take place in an

annually changing set of high schools. I observe 183 events at 83 out of the 142 high schools in Switzerland. Second, students across all grades in the 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.

My preferred event-study specification includes school and graduation-year fixed effects and compares STEM participation in college for students graduating from high school in the years before and after an event, in schools with and without an event. The key identification assumption requires that – after controlling for school and graduation-year fixed effects – STEM participation in schools with an event and schools without an event would move in parallel in the absence of the event. By analyzing detailed annual school reports available for a sub-sample of schools, I confirm that there are no confounding school-level changes, such as other STEM activities or career events, correlated with hosting a *Tecday* or *ETH unterwegs* event. To further enhance the robustness of my analysis, I restrict my 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 in the event study that there are no significant differences in pre-event trends of the outcomes studied.

I find that STEM promotion events increase high-school students' STEM enrollment in college and translate into higher STEM college graduation rates within six years of high-school graduation. The event-study results show that the probability of enrolling in STEM in college increases by 0.91 percentage points (*p-value:* 0.03) for students who graduate from high school in the year of an event, representing a 4.1% increase. These students are also 1.11 percentage points (*p-value:* 0.02) more likely to obtain a degree in a STEM field in college, reflecting a 7.7% increase. Additionally, students who attend an event before their track choice in high school experience a comparable increase in STEM participation in college.

I observe no effect for graduation cohorts that attend events in years without major educational choices (-0.18 percentage points, *p-value:* 0.73)). Together, these findings highlight the importance of timing, suggesting that interventions are most effective when targeted to students facing key educational decisions.

The results are robust to different ways of dealing with the potential negative weighting of the two-way fixed effect estimator. First, I apply the diagnostics by De Chaisemartin and d'Haultfoeuille (2020) to show that none of the weights of my main specification is 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 that the probability of enrolling in STEM increases by 0.93 percentage points, which is very close to my baseline estimate of 0.91 percentage points. Finally, using a stacked approach as in Cengiz et al. (2019), I demonstrate that my results are robust to using only untreated schools as controls.

In the second part of the paper, I exploit quasi-random variation in the event-level share of female speakers to investigate whether female speakers are more effective than male speakers at increasing STEM participation among female students. Previous research often attributes this effect to a role-model mechanism, where female speakers inspire female students through their shared gender, with minimal impact on male students.

I find that female speakers are more effective at attracting students to STEM than male speakers, but that this effect is not differential by student gender. Female students attending events with a high share of female speakers exhibit a 1.88 percentage point (*p-value:* 0.02, +13.00%) increase in the likelihood of enrolling in STEM, whereas the effect on male students is +2.27 percentage points (*p-value:* 0.03). In contrast, low female speaker events do not affect STEM enrollment either of female students (-0.52 percentage points, *p-value:* 0.41) or male students (-0.14 percentage points, *p-value:* 0.89). There is no differential effect of increasing the share of female speakers on male versus female students (*p-value:* 0.82).

What makes female speakers more effective than male speakers at increasing students' STEM participation? I develop a stylized framework showing that attributing the effect of speaker gender to a same-gender role-model mechanism assumes that female and male speakers do not differ along other relevant characteristics that influence students' STEM participation. The observed positive effect of female speakers on male students challenges such an assumption and indicates that female speakers may also influence students' choices differentially through other characteristics.

To investigate these channels, I use rich information on speaker and presentation characteristics that go beyond speaker gender. In particular, I leverage information on presentation content and style, extracted from over 4,000 short presentation descriptions by employing the Large Language Model ChatGPT. I document that female speakers are more likely to use an interactive presentation style, involving students' active participation and the use of supportive presentation tools. Female speakers also tend to be slightly younger and are more likely to cover topics in gender-balanced or predominantly female STEM fields. In contrast, male speakers more often focus on abstract concepts.[1]

Among these observed differences, the interactive presentation style emerges as a key driver of the positive effect of female speakers on students' STEM participation. First, exploiting event-level variation, I find that events with a higher proportion of interactive presentations have a significantly greater impact on students' STEM participation. Second, both female and male students are more likely to mention how they liked their active involvement in feedback for presentations delivered by female speakers. Finally, the effect size of events with a high share of female speakers decreases by 45% and becomes statistically insignificant when controlling for presentation interactivity.

In turn, I provide suggestive evidence that male speakers using an interactive presentation style have a comparable impact on students' STEM participation as female speakers with such a presentation style. When interacting the share of female speakers with the share of interactive presentations, I find that events with a high proportion of interactive presentations but a low share of female speakers increase students' STEM participation to a similar extent as equally interactive events with a high share of female speakers.[2] Finally, further supporting this finding, I show that speakers recognized with an award for excellent teaching — a characteristic uncorrelated with speaker gender — increase both female and male students' STEM participation.

[1]Gender differences in language use are a well-documented pattern, including among politicians (Gennaro and Ash, 2022; Dietrich et al., 2019).

[2]These findings align with social psychology research suggesting that role-model characteristics beyond gender may play a more influential role in shaping students' beliefs (Cheryan et al., 2011; Betz and Sekaquaptewa, 2012).

My results have three important implications. First, brief speaker interventions have a powerful effect on STEM participation for students close to important educational choices, and increase their STEM graduation rates in college in the long run. Second, increasing the proportion of female speakers in such initiatives boosts students' STEM participation but may not substantially narrow the STEM gender gap between female and male students. Finally, selecting speakers directly on presentation quality, instead of speaker gender, results in a comparable impact on students' STEM participation.

I contribute to three strands of literature. First, I add to a recent literature investigating factors contributing to students' STEM participation, such as gender matches between students and teachers or peers (Brenøe and Zölitz, 2020; Mouganie and Wang, 2020; Carlana, 2019; Lavy and Sand, 2018; Lim and Meer, 2017), family dynamics (Anelli and Peri, 2019), or STEM course exposure in high school (Joensen and Nielsen, 2016; Card and Payne, 2021). Cohodes et al. (2022) and Breda et al. (2023) experimentally show that pre-college interventions increase underrepresented high-school students' STEM participation in college. Different from these studies, I investigate interventions on a larger scale both in terms of recipients of the interventions – more than 80,000 students – and speaker characteristics. Moreover, my analysis provides novel evidence that brief interventions have persistent positive effects on students' STEM graduation rates, a key finding to assess their welfare implications.

Second, I contribute to an extensive body of research that uses the gender of political leaders, advisors, teachers, or speakers as a proxy for the effect of same-gender role models (Beaman et al., 2012; Carrell et al., 2010; Card et al., 2022; Bertrand and Duflo, 2017; Lim and Meer, 2017, 2020; Canaan and Mouganie, 2023; Breda et al., 2023; Porter and Serra, 2020; Patnaik et al., 2023). Most of these studies cannot rule out that women and men in the role-model population studied differ along other relevant characteristics that are correlated with gender. My analysis disentangles the effect of gender from such confounders and shows that controlling for them reduces the speaker-gender effect substantially. This finding relates to studies on the impact of teachers' biases correlated with teacher gender, which similarly

offer an alternative channel to the role-model mechanism associated with teacher-gender effects (Carlana, 2019; Lavy and Sand, 2018).

Finally, I add to a literature on the role of information provision in shaping students' college major (Hastings et al., 2015; Conlon, 2021; Bleemer and Zafar, 2018) or occupational choices (Delfino, 2024), which has yielded mixed results. My analysis emphasizes the importance of how information is conveyed, beyond the specific content.

The remainder of this paper is organized as follows. The next sections describe the conceptual framework, the institutional background where the events take place, and the data used in the analysis. Section 5 outlines my empirical strategy. Section 6 shows that students in the last year of high school are more likely to enroll in STEM after attending an event, particularly after events with a high share of female speakers. Section 7 investigates the underlying mechanism for the female-speaker effect. The last section concludes.

2 Conceptual Framework

In this section, I develop a stylized framework to formalize how exposure to potential role models can influence students' college-major choices. I define what constitutes a female role-model effect and discuss how different assumptions regarding the effect of role models' non-gender traits influence mechanism identification and the expected impact on the gender gap in study choices. The framework builds on the college-major choice models by Altonji (1993), Altonji et al. (2016), Zafar (2013) and Hastings et al. (2015).

Choice model Students are of gender female f or male m. At the initial period $t = 0$, students are enrolled in high school and have not chosen a college major. Between period 0 and 1, each student i is randomly exposed to a treatment T consisting of a presentation by an expert of gender G female F or male M. Beyond their gender G, the experts have non-gender characteristics I. In the empirical section of this paper, I will consider non-gender characteristics such as age, speaking experience, presentation topics and several measures capturing presentation style.

In period 1, student i is confronted with the decision to choose a college major j from her choice set J. Payoffs for each of the choices depend on the student's major-specific outcomes CL_{ij} that are realized in college or after graduating from college. The choice-specific outcomes CL_{ij} are uncertain in period 1. In period 1, student i therefore possesses subjective beliefs λ_{ij1} about the payoffs associated with the choice of major j for all $j \in J$. The choice problem for individual i in period 1 is:

$$\max_{j \in J_i} U_{ij1} = \lambda_{ij1} CL_{ij}$$

Exposure to potential role models In period 0, student i has beliefs λ_{ij0} about the choice-specific outcomes CL_{ij}. I assume that the potential role models can influence students' beliefs separately by τ_{ijT}, which is a function of $f(G)$, and ρ_{ijT}, which is a function of $f(I)$. When assuming that beliefs are additive, λ_{ij1} can be rewritten as $\lambda_{ij1} = \lambda_{ij0} + \tau_{ijT} + \rho_{ijT}$.

Depending on treatment status T_i, student i associates the following utility with major j in period 1:

$$U_{ij1} = \begin{cases} (\lambda_{ij0} + \tau_{ijF} + \rho_{ijF}) CL_{ij}, & \text{if } T_i = F. \\ (\lambda_{ij0} + \tau_{ijM} + \rho_{ijM}) CL_{ij}, & \text{if } T_i = M. \end{cases}$$

In potential outcomes notation, student i experiences the following effects on her expected utility U_{ij1} if randomly exposed to different treatments T:

$$ATE = \underbrace{E[U^1_{ij1}|T_i = F] - E[U^0_{ij1}|T_i = M]}_{\text{effect of being exposed to a F instead of M speaker}} = \underbrace{(\tau_{ijF} - \tau_{ijM}) CL_{ij}}_{\text{due to speaker gender}} + \underbrace{(\rho_{ijF} - \rho_{ijM}) CL_{ij}}_{\text{due to other channels}}$$

For the remainder of this chapter, I assume that the potential role models influence students' beliefs only in $j = STEM$ and for parsimony drop the subscript j from notation.

Definition of female role model effects Prior research has attributed the positive effects of female leaders, teachers, advisors, or speakers on female students' attitudes and choices toward male-dominated fields to a role-model mechanism (Beaman et al., 2012; Breda et al.,

2023; Canaan and Mouganie, 2023; Porter and Serra, 2020; Patnaik et al., 2023).

Building on the previously outlined framework, I define such female role-model effects on female students as $(\tau_{fF} - \tau_{fM})CL_f > 0$, i.e. female experts increase female students' beliefs more than male experts through their gender G. If also $(\tau_{mF} - \tau_{mM})CL_f < 0$, i.e. female experts increase male students' beliefs less than male experts, then there is a same-gender role-model effect. For the following, I assume that there is either a female role-model effect on female students or a same-gender role-model effect on female and male students but rule out the possibility of an opposite-gender role-model effect.

There are two main reasons to define the role-model effect in this way. First, although often not explicitly defined, the mechanism builds on a concept from social psychology where leaders, who are issued from a minority group, might affect the attitudes of members of this group about their own ability to succeed or their aspirations to do so (Bertrand and Duflo, 2017; Chung, 2000). In our case, the minority group – female students – is defined by gender. Seeing successful women in traditionally male-dominated fields may lessen stereotype threat for female students, thereby improving their aspirations and increasing their likelihood of entering these fields (Beaman et al., 2012). Second, the adopted definition captures the main feature of role models in the minds of many people who use the term. When designing speaker interventions targeted to female students, both researchers and practitioners typically select potential role models based on gender (see interventions with only female speakers, as in Breda et al. (2023) or Porter and Serra (2020)).

So far, I have focused on the size of $(\tau_{ijF} - \tau_{ijM})CL_{ij}$. Next, I will discuss three cases to illustrate the assumptions for $(\rho_{ijF} - \rho_{ijM})CL_{ij}$ that are necessary to identify the role-model mechanism and for female speakers to reduce the gender gap in study choices.

Case 1: No effects of non-gender characteristics Equation (2) illustrates that random exposure to potential role models can not only shift students' beliefs through expert gender $(\tau_{fF} - \tau_{fM})$ but also through other non-gender expert characteristics $(\rho_{fF} - \rho_{fM})$.

If we adopt the assumption

$$\rho_{iT} = 0,$$

i.e. female and male speakers do not affect students' beliefs through their non-gender characteristics, then $E[U_{i1}^1|T_i = F] - E[U_{i1}^0|T_i = M] = (\tau_{iF} - \tau_{iM})CL_i$. In this case, exposure to female instead of male experts increases female students' utility U_{f1} and reduces the gender gap in STEM enrollment because male students are either less likely to pursue the fields or remain unaffected. Furthermore, the effect of being exposed to female instead of male experts on female students can be fully attributed to the role-model effect.

Assumption (2) appears most applicable in scenarios like those investigated by Beaman et al. (2012), where potential female role models, such as village leaders, lack direct contact with students. Furthermore, studies on interventions featuring exclusively female experts such as Porter and Serra (2020) or Breda et al. (2023) rely on $\rho_{fF} = 0$ to infer the role-model mechanism.

Case 2: Same effects of female and male non-gender characteristics $\rho_{fT} = 0$ is a strong assumption for settings involving students' exposure to teachers, advisors or speakers, given the direct interaction between students and the potential role models. Information provision is an inherent part of short interventions involving speakers who deliver talks about their careers (Breda et al., 2023; Porter and Serra, 2020). A less restrictive assumption is:

$$\rho_{iF} = \rho_{iM},$$

i.e. female and male speakers have the same effect on students' beliefs through their non-gender characteristics I. This less restrictive assumption cancels out ρ_{fF} and ρ_{fM} for situations where students are exposed to both female and male experts, such as the student-teacher interactions studied in Card et al. (2022), Carrell et al. (2010) or Lim and Meer (2017). As in the previous case, exposure to female instead of male experts increases female students' utility U_{f1}, reduces the gender gap in STEM enrollment, and the effect can be fully

attributed to the role-model mechanism.

Case 3: Differential effects of female and male non-gender characteristics Finally, we can adopt the assumption:

$$\rho_{fF} > \rho_{fM}, \quad \rho_{mF} = \rho_{mM},$$

i.e. female experts have a stronger effect than male experts on female students' beliefs through their non-gender characteristics I, while female and male experts have the same effect on male students' beliefs through their non-gender characteristics I. As in the previous scenarios, exposure to female instead of male experts increases female students' utility U_{f1} and reduces the gender gap in STEM enrollment. However, unlike the earlier cases, the effect on female students is a combination from both the role-model influence of female experts and their non-gender characteristics.

This paper provides multiple pieces of evidence suggesting that the three described assumptions are unlikely to hold for the speaker interventions studied. First, I demonstrate that both female and male students are more likely to enroll in STEM after attending events with a higher proportion of female speakers. Second, I show that female speakers differ from male speakers in the way they deliver their presentations and are more likely to emphasize students' active engagement. Third, I document that events with a high share of interactive presentations have a stronger effect on both female and male students' STEM participation and that both female and male students are more likely to positively mention active participation in their feedback to presentations delivered by female than male speakers. Finally, I show that the effect size associated with high female-speaker share events decreases by 45% after controlling for interactive presentation styles. Together, these results indicate that female speakers influence students' study choices through their non-gender characteristics ($\rho_{iF} > 0$) and that this influence is greater than that of male speakers' non-gender characteristics ($\rho_{iF} > \rho_{iM}$) for both female and male students.

3 Setting

In this section, I briefly summarize the key features of the events studied in this paper and the institutional background in which the events 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 students to specific STEM study fields available at the university. Presentations are delivered by speakers from ETH faculty and typically focus on a topic related to their research. Presentations take place 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 have to attend the presentations. On average, a presentation has a duration of 45 minutes and students attend 6 presentations per event sequentially. Over the 107 *ETH unterwegs* events that are part of the analysis, 248 unique speakers participated in the events, with 7 percent of the speakers being female.

Tecdays are similarly aimed at promoting STEM among high-school students but do not focus on a specific university. Speakers are both from academia and industry. Furthermore, in contrast to *ETH unterwegs* events, students specify the sessions they are interested in attending. Specifically, from on average 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. 1,250 unique speakers participate in the 76 *Tecdays* that are part of the analysis. The average female speaker share per *Tecday* is 23 percent.

Institutional Background The events take place within the Swiss academic high school system, designed to prepare students for higher education. Typically, students enter academic high school at the age of 14, following lower secondary school. Depending on the federal state, students either select a specialization track at this point or at a later grade.

Two tracks emphasize STEM subjects: 'Physics and Mathematics' and 'Biology and Chemistry'. The other offered tracks focus on languages, economics, law, or arts. Admission to Swiss academic high school is selective, contingent on either lower secondary school grades or success in an entry exam. Only 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 high school graduation. Students already have to select their college major at this point, before they start their tertiary studies.

Two features make the 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. Second, all universities and tertiary study programs require a similar low semester fee. Together, these features allow 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 high-school graduates proceed directly to university, while an additional 40% start their tertiary studies after a gap year. 27.6 % of male high-school students and 10.5% of female high-school students enroll in a STEM study field in college within 2 years of graduating from high school.

4 Data

I use information from three sources: event flyers, Swiss administrative education data, and students' feedback surveys. This section describes the data sources and key variable definitions.

4.1 Event and Presentation Data

I have collected and digitized event flyers from ETH Zurich and the Swiss Academy of Engineering Sciences for all events that have taken place from the inception of the event series in 2006 and 2007, respectively, to the end of the school year 2019/20. In total, the data comprises 183 events, involving 1,500 speakers, delivering 4,500 presentations.

I digitize the event flyers to obtain information about the school and the date each event takes place as well as to gather information on the speakers and presentations at each event. The flyers clearly separate the event date, school name, speaker name, presentation title, and, in the case of *TecDays* events, presentation description. Figures A1 and A2 in the Appendix display exemplary flyers.

Event timing Events occur throughout the academic year that starts in mid-August and ends in mid-July the following calendar year. As high-school students have to enroll in a tertiary study program by April 30 of their senior year, I use this date as the relevant cutoff to allocate event dates to academic years.

Speaker gender Using data from the Swiss Federal Statistics Office on the frequency of all first names in the Swiss population by gender in the year 2021, I infer speaker gender from each speaker's first name. I verify that I classify speaker's gender correctly by comparing the inferred gender of speakers from ETH faculty to their gender administratively recorded by ETH Zurich.

Speaker age For speakers at *ETH unterwegs* events, I obtain administrative data of ETH Zurich that records the birth year of each speaker. This allows me to measure the age of the speakers at the time of their event participation.

Presentation topic I classify each presentation topic based on its presentation title. To classify the titles, I follow the International Standard Classification of Education (UNESCO,

2015). The classification provides classification guidelines for each field and allows the mapping of presentation topics to tertiary study program choices in the administrative data.

Presentation content and style In the following, I describe tools I use to classify the presentation descriptions available for 4,000 *TecDays* presentations.

Text classification using ChatGPT I employ the Large Language Model of the ChatGPT API environment to classify the presentation descriptions in terms of content and style. I identify potential classification dimensions from a manual that the Swiss Academy of Engineering Sciences provides to prospective speakers with recommendations on how to deliver enthusiastic and inspiring accounts to high-school students. The manual recommends (i) topics relevant to students' experience (ii) interactivity and dialogue with students (iii) the use of supportive learning tools or materials (iv) explanation of one's profession and career path. The dimensions are similar to the key elements identified by Bayer et al. (2020) for the Harvard course "Using Big Data to Solve Economic and Social Problems" taught by Raj Chetty, which aims to diversify the pool of undergraduates who study economics.

For each of the dimensions, I construct a separate prompt. The exact prompt I use to classify whether the presentation involves students' active participation reads:

> 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 student's 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.

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 de-

veloping 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 beenn show to restrict hallucinations and to improve its accuracy. The text classification is described in more detail in Appendix A.[3]

Speaker quality and experience Due to the large number of events, speakers participate multiple times in events. To proxy speaker experience, I count for each speaker's event appearance the number of presentations delivered by the speaker in the past. For the event series *ETH unterwegs*, I additionally assess speakers' teaching quality by matching speakers to recipients of ETH Zurich's Golden-Owl award for outstanding teaching. This annual award, determined through student evaluations at ETH Zurich, is awarded to the highest-rated faculty member in each department.

4.2 Swiss Administrative Data

I link the event data to student-level administrative data on the full population of high-school graduates and their university careers in Switzerland. The key advantage of this data is its extensive temporal coverage, allowing the tracking of student outcomes throughout university. Table 1 provides the summary statistics. The data covers college outcomes of all 353,418 students graduating from 142 different schools between the academic years 1999/00 and 2019/20. 57.5 percent of graduates are female. For students graduating after 2007, the data also provides information on students' high-school specialization.

Here, I define the primary outcomes I use in my analysis.

[3]I use the parameters 'precision' and 'recall' to evaluate the performance of ChatGPT. In comparison to a hand-coded subsample of presentation descriptions for 2 dimensions of presentation interactivity, ChatGPT has 91.6% precision and 78.5% recall. In other words, 8.4% of the presentations ChatGPT identifies as having an interactive presentation style may not, when taken the hand-coded data as the truth, involve interactivity (a false positive), while ChatGPT may neglect to identify one in four presentations involving interactivity (a false negative).

STEM enrollment STEM enrollment is measured with a dummy variable that takes a value of 100 if a high-school student enrolls within 2 years of high-school graduation in a STEM study field at a tertiary institution and 0 otherwise. I measure enrollment within 2 years of high-school graduation to increase comparability of later to earlier graduation cohorts. I classify study programs following the International Standard Classification of Education (ISCED) classification system (UNESCO, 2015). STEM study fields belong to the following ISCED fields: natural sciences, mathematics, and statistics (ISCED-05), information and communication technologies (ISCED-06), and engineering, manufacturing, and construction (ISCED-07). To examine different gender dynamics, I categorize STEM study fields in which female university students constitute less than 40% of enrolled students as predominantly male STEM fields and STEM fields with a female students share of 40% or higher as gender balanced or predominantly female. Similar STEM classifications have been used by Brenøe and Zölitz (2020) or Anelli and Peri (2019). Table A2 in the Appendix describes the STEM study fields identified and categorized in this way. Figure A3 plots the raw STEM enrollment data and event data for a single school.

STEM graduation Analogously to the variables measuring STEM enrollment, I create a dummy variable that takes a value of 100 if a high-school student obtains an undergraduate degree within 6 years of high-school graduation in a STEM study field at a tertiary institution and 0 otherwise.

Gender gap in STEM enrollment To directly analyze the impact of the intervention on the gender gap in STEM participation, I aggregate the data to the school s and graduation-year t level. I then compute the conversion ratio of female high-school (HS) graduates enrolling in STEM in college to the total HS graduates enrolling in STEM in college, normalized by the female to total HS graduates ratio for school s in graduation year t, as given by the following equation:

$$\text{Conversion Ratio}^{\text{FT}}{}_{\text{st}} = \frac{\text{(Female HS graduates in STEM in college / Female HS graduates)}}{\text{(Total HS graduates in STEM in college / Total HS graduates)}}$$

This ratio is similar to the one employed by Avilova and Goldin (2023). If the intervention increases STEM enrollment more strongly for female than male students, the conversion ratio will increase.

4.3 Presentation Feedback Surveys

The Swiss Academy of Engineering Sciences administers feedback surveys to students after each event. Students answer an open-ended question about what particularly impressed them about each presentation. The data is available for 38 events and comprises 21,605 responses from 8,085 students. I utilize the Large Language Model ChatGPT to extract structured information from these responses, following the same procedure and focusing on the same dimensions as described in 4.1.

5 Empirical Strategy

I conduct my analysis at the student level, estimating whether a STEM event leads to an increase in the probability that student i graduating from school s in school year t enrolls or graduates in a STEM study field in college after high school graduation.[4] As my baseline specification, I estimate a dynamic event study two-way fixed-effects regression (event study TWFE). The event study allows me to check for differential trends before a STEM event and after all students who attended an event have graduated from a school. Second, it enables me to precisely estimate when the effect of the STEM events materializes, which is particularly important given that students across all grade levels attend the events.

The event study 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

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

in my setting correspond to a staggered, non-absorbing treatment, where schools can be treated multiple times. Out of the 142 schools, 59 schools host no event, 30 host one event, and 53 schools 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 4 years before to 5 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 4 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 5 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 A1 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, my 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 move to a static two-way fixed-effects regression (static TWFE) that is informed by the dynamic results and that is of the following form:

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

In this specification, my main parameter of interest is $Event_{st}^{0}$, which takes a value of 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 1 year before an event and $Event_{st}^{(1,13)}$ equals the number of past events for students who graduate more than 1 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 and all cohorts in the

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

My specification requires two key assumptions to causally identify the effects of the events. First, schools should not respond in anticipation of a future event (*no anticipation*). Second, the specification requires that after controlling for school and graduation-year fixed effects, STEM enrollment in schools with an event and in schools without an event would move in parallel in the absence of the 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. This concern is particularly important as school principals reach out to the event organizers to schedule events and therefore endogenously select their schools into treatment.

To assess the validity of the identification assumptions, I proceed as follows. First, I show that there are no confounding school-level changes correlated with hosting a *Tecday* or *ETH unterwegs* event. This analysis is based on 244 detailed school calendars taken from annual school reports, available for 26 schools (see Figure A4 for an example). While I find a significant positive effect of 0.89 on the likelihood that a report mentions a *Tecday* or *ETH unterwegs* event in the year of the event, Table 2 shows no effects on the likelihood to organize other STEM activities or host any career or study information events in the year when they host a *Tecday* or *ETH unterwegs* event. Furthermore, I document that *ETH unterwegs* events increase STEM enrollment specifically at ETH Zurich, further supporting the conclusion that there are no school-level changes correlated with the events of interest. Second, I narrow my analysis to the 83 schools hosting at least one event. As this in turn can lead to issues with the two-way fixed effect estimator (Baker et al., 2022), I show in Table 4 that the results are consistent but slightly more conservative than results based on all 142 schools. Finally, I use the event study specification to demonstrate the absence of differential trends in STEM enrollment probabilities across schools before a STEM event.

As shown by De Chaisemartin and d'Haultfoeuille (2022) and Dube et al. (2023), speci-

fications with non-absorbing treatments as the repeated events present in this study require an additional assumption regarding the duration until the dynamic effects stabilize (*effect stabilization*). In Section 6, I show in the event-study analysis that the increase in the probability that a high-school student enrolls in STEM in college materializes immediately for students facing an educational choice in the same year. Students who graduate in the same year that they attend an event or who pick their specialization choice in high school in the same year are more likely to later pursue STEM in college. I do not find effects on other graduation cohorts.

Recent econometric literature has identified potential issues with the two-way fixed effect estimator used in this study 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., 2023). Given the immediate effects of the events, we would anticipate minimal TWFE biases (Baker et al., 2022). Indeed, as shown in Section 6, I find that my results are not subject to negative weights, following the diagnostics proposed in the literature, and demonstrate that the effects of the TWFE estimator are consistent with the alternative robust estimator proposed by Sun and Abraham (2021). I also show that my results do not depend on the selection of control schools and document similar effects when I only use schools without any event as controls.

6 STEM Participation Across all Events

6.1 Dynamic Event-Study Results

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

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*: 0.02) or 4.2 percent 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 A3 in the Appendix, the secondary effect for students graduating from high school 3 to 4 years after attending an event is concentrated at the 34 high schools in the sample that allow students to choose their high-school specialization after entering the school (in the other 49 high schools, students select school and track simultaneously).[5] Similarly Table A4 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 high-school 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 1 to 2 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; Dynarski et al., 2021; Patterson et al., 2019).

Finally, the effect fades away for students graduating 5 or more years after an event. Given that high school typically lasts 4 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 event series *ETH unterwegs* has a focus on introducing high-school students to the STEM study fields available specifically at ETH Zurich. To further increase confidence in

[5]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.

my identification assumption, 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 either in the year of high-school graduation or before their specialization choice become significantly more likely to enroll in STEM at ETH Zurich (+0.77, *p-value:* 0.01; +0.99, *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).

6.2 Static DiD Results

Table 3, column(1) displays the results from the static TWFE specification in equation (2) for the 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 allows following 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 were only able to analyze students' enrollment decisions rather than their study success. In Table 3, column (3) I present 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. 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 percent terms, the events have a slightly stronger effect on STEM graduation than on STEM enrollment, indicating that the students who are induced by the events to pursue STEM studies are at least as successful as the students who pursue STEM in college in the absence of an event. I corroborate the findings on obtaining a STEM degree also in the dynamic event-study setting, displayed in Figure A7.

I then split the sample by student gender and distinguish between predominantly female or gender-balanced STEM fields and predominantly male STEM fields. Figure A8 shows that, while there are no discernible differential effects by student gender on overall STEM

enrollment, 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 to enroll in gender-balanced or predominantly female STEM study fields. Conversely, male students are significantly more likely than female students to enroll in predominantly male STEM study fields.

I next analyze which study fields the STEM promotions events are attracting students away from. In Table A5, I examine how the events affect enrollment in (3) business and law, (4) arts humanities, (5) education, (6) social sciences, and (7) health sciences. The results suggest that students exposed to a STEM promotion event most likely substitute health studies with STEM, although the size of the point estimate can not fully equalize the increased enrollment in STEM, suggesting that students are also nudged away from fields such as social sciences. STEM promotion events do not influence students' probability of enrolling in business and law, arts and humanities, and education.

Finally, Table A6 reveals that the impact of the events on students who attend an event and graduate from high school in the same year is particularly concentrated among those 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 informed beliefs about pursuing STEM studies at the college level prior to attending the events.

6.3 Robustness

In settings where treatment is staggered, treatment effects are heterogeneous and there are dynamic treatment effects over time, the two-way fixed effects estimator is a weighted average of heterogeneous group-specific treatment effects where the weights may be negative, leading to potential bias (Dube et al., 2023). The bias arises because previously treated units are implicitly used as controls for newly treated units, although they might still be experiencing lagged time-varying and heterogeneous treatment effects.

To address concerns regarding these potential biases, I conduct several robustness tests.

I show that there are no negative weights in my TWFE baseline specification. 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. In Table 4, column(3), I find 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.[6]

Moreover, I confirm that my 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. Table 4, column (4), extends the estimation sample to schools without any event. Column (5) implements 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 utilize untreated schools as controls.

My results are robust to alternative ways to deal with outcome dynamics in schools with events. First, the events increase STEM enrollment by 0.96 percentage points when I include linear school-specific time trends to my baseline specification (column (5)). Second, the effects do not change when I implement a simple DID specification in which from treated schools I only include students who graduate just before and after an event. Furthermore, in column (7), 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 close to my baseline specification.

Finally, to demonstrate 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, providing further confidence in the reliability of the TWFE estimate.

[6]Figures A5, A6, and A7 in the Appendix replicate the dynamic results following the estimation procedure by Sun and Abraham (2021).

7 Exposure to Female Speakers

7.1 Effects on STEM Participation

My 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 event-level variation in female speaker shares to investigate empirically whether female speakers are more effective than male speakers at increasing STEM participation. To schedule speakers for the events, the event organizers reach out to their speaker network. Due to speaker availability constraints, female speaker composition varies across events and ranges from 0% to 40% across events. Figure A10 shows the distribution of events by female speaker composition. In the regression specification of equation 2, I divide events into events with a low and a high share of female speakers akin to a triple difference estimation. Table A7 shows that female-speaker share is not correlated with other event-level observables, such as number of speakers per event or event month.

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 1.71 percentage points (*p-value:* 0.007, +7.65%) more likely to enroll in STEM, while events with a low female speaker share do not have any detectable effect on STEM enrollment (-0.35 percentage points, *p-value:* 0.53, -1.57%). Moving again to the static event-study design, I show 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, +11.2%) more likely to obtain a STEM undergraduate degree.

Figure A11 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 1.88 percentage point (*p-value:* 0.02, +13.00%) increase in the likelihood to enroll in STEM. Female students are also more likely to

enroll in predominantly male STEM subfields. However, the effect can be mainly attributed to increased enrollment in predominantly female STEM fields (+1.62 percentage points, *p-value:* 0.01). The estimates for events with a low share of female speakers are not significant and tend towards zero or negative values (for STEM enrollment: -0.52 percentage points, *p-value:* 0.41).

Similarly to female students, male students are significantly more likely to enroll in STEM after attending events with a larger share of female speakers. Male students attending events with a high share of female speakers are 2.26 percentage points (*p-value:* 0.03, +6.88%) more likely to enroll in STEM, versus an effect of -0.14 percentage points (*p-value:* 0.89) for events with a low share of female speakers. The positive effect of female speakers on male students' STEM enrollment is driven by their significantly larger enrollment in predominantly female STEM fields. Male students who attend an event with a low share of female speakers exhibit a 1.59 percentage point (*p-value:* 0.02) decrease in the likelihood of enrolling in predominantly female STEM fields. Events with a high share of female speakers turn this effect positive (+0.77 percentage points, *p-value:* 0.12), with the difference between the impact of events with a low and a high share of female speakers being significant at the 0.01-level.

Figure A12 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, 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 A12 is the absence of any discernible treatment effect on the gender gap for either type of event.

7.2 Mechanisms: Is it all about a role-model effect?

In this section, I explore why events with a larger share of female speakers increase students' likelihood to enroll 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, where female speakers inspire female

students through shared gender (Beaman et al., 2012; Card et al., 2022). The positive effect of female speakers on male students challenges such an interpretation and indicates that female and male speakers might also influence students' study choices through distinct non-gender characteristics that are correlated with speaker gender. In particular, the results presented so far suggest that female speakers influence students' study choices through their non-gender characteristics ($\rho_{iF} > 0$) and the impact of female speakers' non-gender characteristics is greater than that of male speakers' non-gender characteristics ($\rho_{iF} > \rho_{iM}$) for both female and male students. In the following, I investigate such alternative channels.

First, I examine whether female and male speakers differ across other non-gender characteristics that may influence student outcomes. To do so, I extract structured information from a unique sample of 4'000 presentation descriptions by applying the Large Language Model ChatGPT, as described in Section 4. The data reveals 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, as well as on their feedback regarding the presentations.

Are there speaker or presentation characteristics correlated with female speaker gender? Previous research has faced limitations in untangling the impact of gender from other characteristics, either due to the exclusive presence of female speakers in interventions or because of the small number of speakers overall. Similarly, studies on the effects of long-term exposure to female teachers or advisors often lack detailed data on student-teacher interactions or advising practices (Canaan and Mouganie, 2023). Figure 4 investigates whether specific speaker or presentation characteristics correlate with female-speaker gender.

For the speakers participating in the *ETH unterwegs* intervention, I measure various characteristics, such as age, academic titles, or teaching awards. The data reveals that, on average, female speakers are slightly younger than their male counterparts and participate less frequently in the events. However, there is no significant difference between female and male speakers in terms of holding a professor title. Furthermore, the likelihood of receiving

a teaching award – granted by ETH Zurich based on student surveys – does not significantly differ between male and female speakers[7].

Turning to the presentation attributes, I identify significant differences in style between female and male speakers. Categorizing presentations with the International Standard Classification of Education (ISCED) classification system, I find that female speakers are more likely to present in predominantly female or gender-balanced STEM fields. Furthermore, female speakers tend to adopt more interactive presentation methods, including encouraging collaboration among students, fostering active participation, and utilizing supportive learning 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.

Do gender-correlated attributes increase STEM participation? In this section, I examine the impact of speaker characteristics, for which gender differentials were observed, on students' likelihood to enroll in STEM fields. Figure 5 illustrates the effects of 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, which involves student participation, collaboration, and the use of learning tools.

When I categorize events by the proportion of presentations in female-friendly STEM fields, no significant differential effect on STEM enrollment is observed. 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 proportion of presentations with an interactive style have a significantly greater impact on students' STEM enrollment compared to events with a lower share of such presentations.

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

I corroborate this finding by an analysis of students' presentation feedback surveys, administered by the Swiss Academy of Engineering Sciences. The analysis is based on surveys from 38 events, comprising 29,775 responses from 9,484 students. Students are asked in an open-ended question what has particularly impressed them about each attended presentation. I classify the answers using ChatGPT as described in Section 4. I measure which presentation characteristics students are more likely to mention in feedback to female instead of male speakers. The results, displayed in Figure 6, indicate that both female and male students are significantly more likely to positively highlight interactive features in presentations by female speakers compared to those by male speakers.

I demonstrate that the point estimate for events with a high female-speaker share is reduced when controlling for the proportion of interactive presentations. Table 5 presents the results, focusing on the effects of *Tecdays*, the events for which the presentation descriptions are available. After accounting for the share of interactive presentations, the point estimate for *Tecday* events with a high female-speaker share decreases from 2.73 percentage points (*p-value*: 0.058) to 1.51 percentage points (*p-value*: 0.245), representing a 45% reduction compared to the estimate obtained without this control. In contrast, the point estimate for events with a high share of interactive presentations is 2.78 percentage points and significant (*p-value*: 0.028).

Finally, I provide suggestive evidence that male speakers using an interactive presentation style have a similar impact on students' STEM participation as female speakers with such a presentation style. I divide events by their female-speaker share as well as their share of presentations with an interactive presentation style. Figure 7 shows that the larger effect of events with a high share of interactive presentations is driven by both events with a low and a high share of female speakers.

Which other speaker attributes influence students' STEM participation? I use information on who of the ETH faculty speakers participating in the *ETH unterwegs* intervention has been awarded a prize for excellent teaching at ETH Zurich. At the end of each

spring semester, ETH Zurich's students association sends an online survey to all students enrolled at ETH Zurich, asking them to rate the teaching style of the lecturers whose courses they have attended. Students rank the teaching style of each lecturer from bad to excellent using a 10-point scale. Based on the survey results, one lecturer per department is then selected for the award. I have access to data on all 251 lecturers who have been awarded since the inception of the Golden-owl award in 2005. Based on this data, I identify all speakers participating in the intervention *ETH unterwegs* who receive awards between 2005 and 2020. Figure A13 shows the results from the analysis of whether events with a large share of awarded speakers are more effective at increasing STEM enrollment. I find that *ETH unterwegs* events with a large share of speakers recognized for excellent teaching have a positive effect on students' STEM enrollment and the effect is significantly larger than of events with a low share of awarded speakers.

8 Conclusion

Increasing enrollment in STEM fields benefits both individuals, through higher earnings (e.g., Kirkeboen et al. (2016)), and society, by addressing skill shortages and fostering innovation (e.g., OECD (2017)). However, in most OECD countries, women remain underrepresented in STEM disciplines. Promoting female role models is frequently proposed as an effective strategy to increase female participation in male-dominated fields such as STEM (Breda et al., 2023; Porter and Serra, 2020).

This study provides evidence that exposure to STEM promotion events significantly boosts both female and male students' later enrollment and graduation in STEM in college. Events with a higher proportion of female speakers have a more pronounced positive effect on female students' STEM participation. However, the positive impact of increasing the share of female speakers also extends to male students, who become equally more likely to enroll in STEM fields. This effect on male students challenges the notion of a pure role-model mechanism, where female speakers inspire female students through shared gender.

Further analysis suggests that the interactive presentation style, more frequent among female speakers, is an important factor driving increased STEM participation for both female and male students.

This study demonstrates that brief, cost-effective interventions can significantly increase high school graduates' enrollment and graduation rates in STEM in college. The analysis underscores that increasing the proportion of female speakers in such interventions can enhance their overall effectiveness. However, as this effect is driven by speaker attributes beyond speaker gender, selecting speakers directly on presentation quality results in a comparable impact on students' STEM participation.

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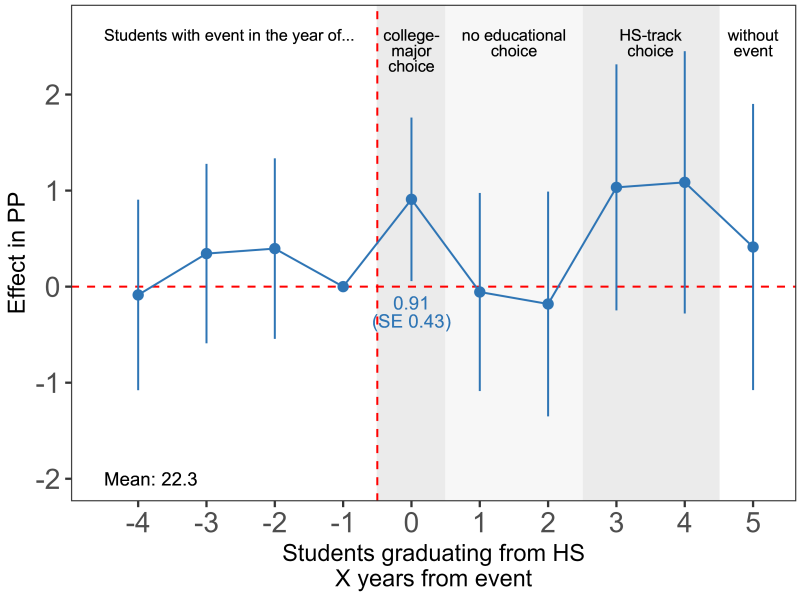
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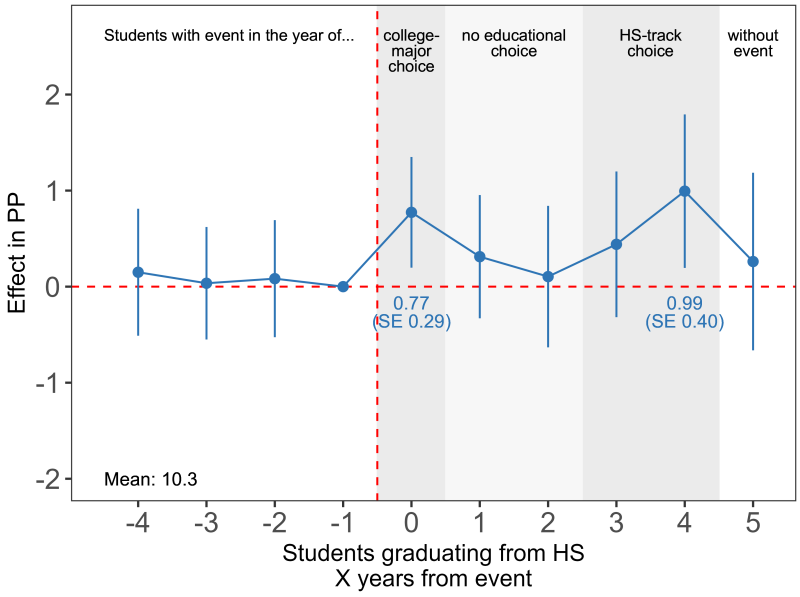
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Figures



(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).

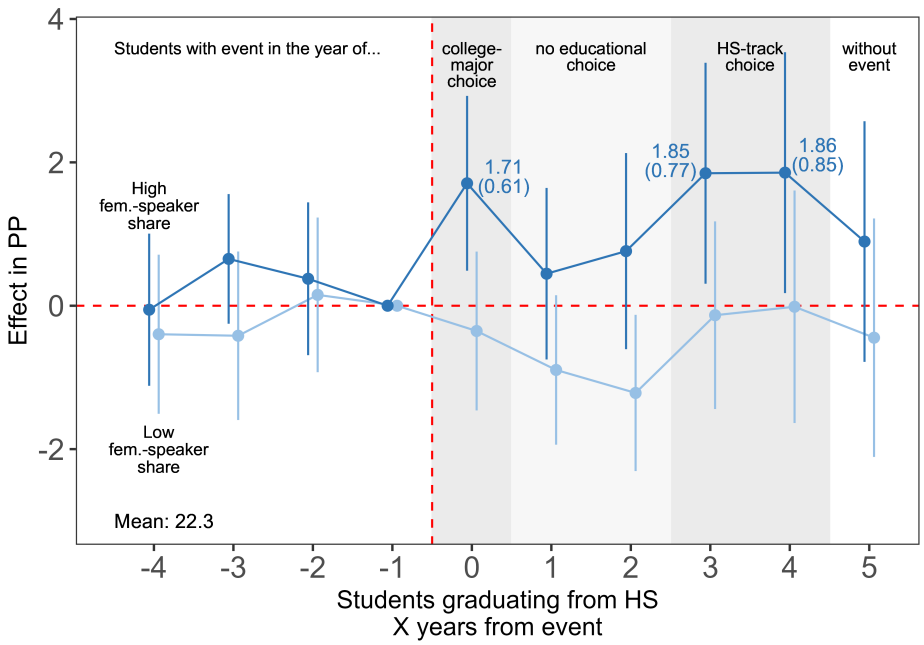


Figure 2: Impact of STEM Events With a High Share of Female Speakers on the Probability of Enrolling in STEM in College

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.

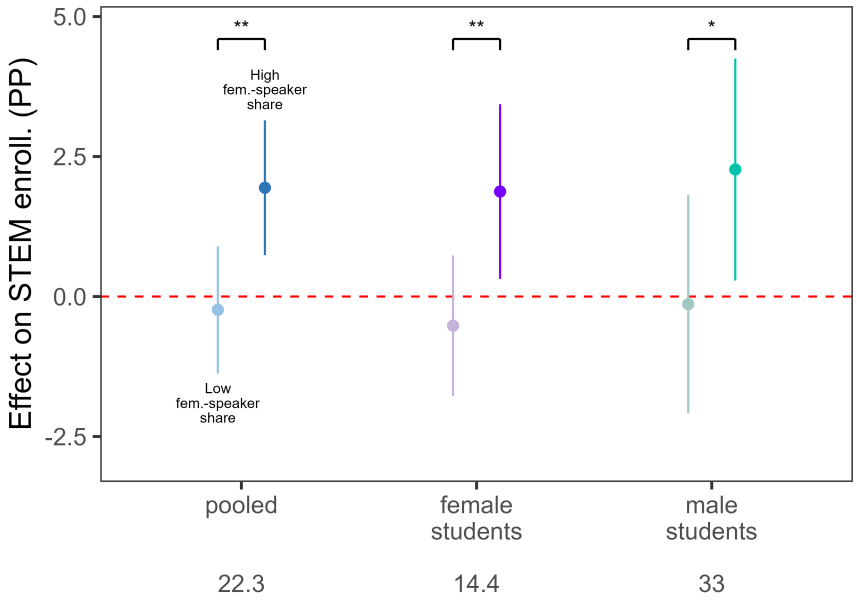


Figure 3: Impact of Event-Level Variation in Female-Speaker Share on the Probability of Enrolling in STEM in College

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. 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

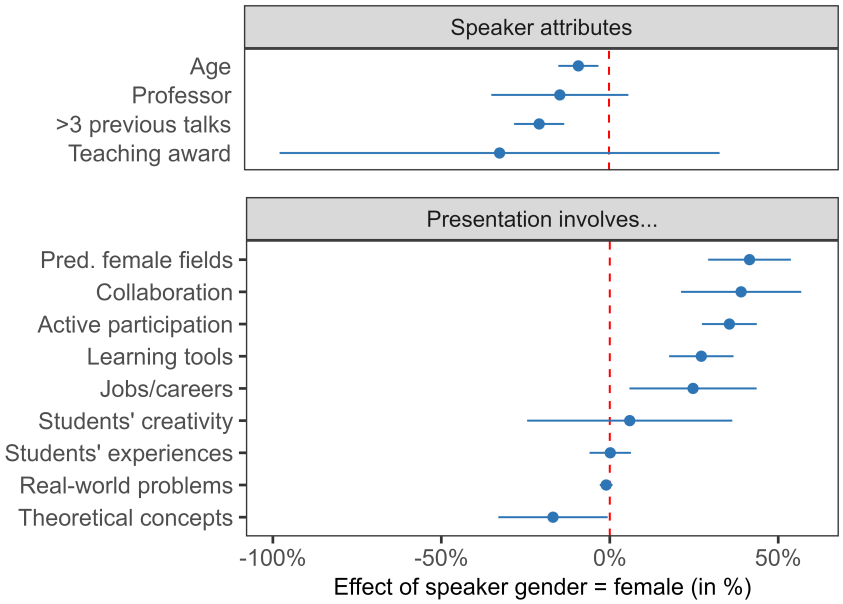


Figure 4: Differences in Speaker and Presentation Characteristics by Speaker Gender

Notes: This figure presents standardized point estimates and standard errors from bivariate regressions of various speaker and presentation characteristics on a dummy for female speakers. The analysis includes 4,838 presentations from 107 *ETH unterwegs* and 76 *Tecdays* events held between 2006 and 2020. Presentation field and speaker experience data are available for both interventions. Variables such as speaker age, teaching award status, and professor title apply only to *ETH unterwegs* events, while presentation style data is specific to *Tecdays* events and based on presentation descriptions. Standardization by respective means allows for effect size comparability across regressions.

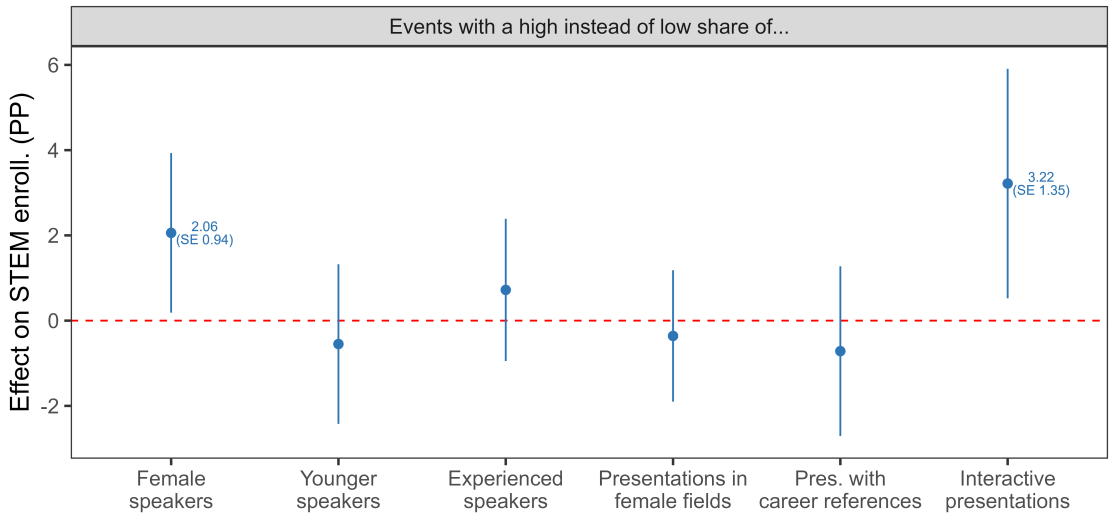


Figure 5: Impact of Gender-Correlated Speaker and Presentation Characteristics on STEM Enrollment in College

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 held between 2006 and 2019. Effects compare 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. Interactive presentations are defined as those incorporating active participation, student collaboration, or learning tools. The figure presents OLS coefficients with 95% confidence intervals (indicated by vertical lines), with standard errors clustered at the school level.

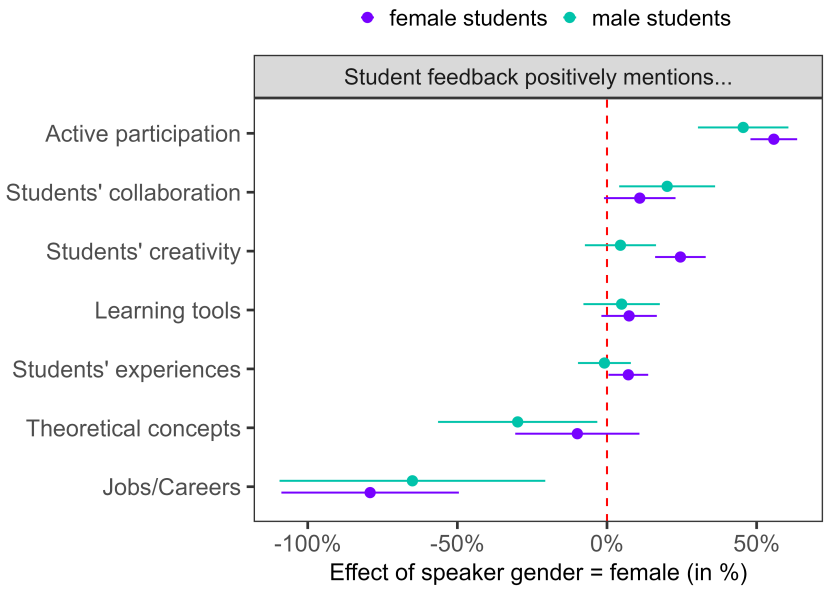


Figure 6: Presentation Characteristics More Frequently Cited in Student Feedback for Female vs. Male Speakers

Notes: This figure displays OLS coefficients from bivariate regressions examining whether specific presentation characteristics are mentioned more frequently in feedback for female 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 4. OLS coefficients with the 95% confidence interval (vertical lines) are displayed.

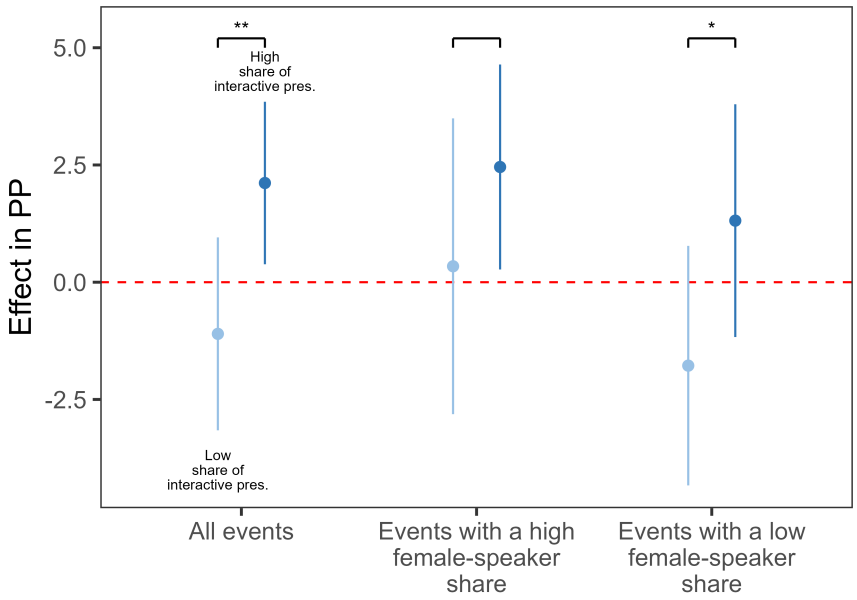


Figure 7: Impact of Event-Level Variation in Interactive-Presentation Share on STEM Enrollment, by Female-Speaker Share

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 learning 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

Tables

Table 1: Summary Statistics

Variable	Count	Mean	Std. dev.	q10	q90
All high-school (HS) graduates					
Female student	239,299	57.6	49.4	0	100
Public school	239,299	99.5	7.3	100	100
Language region					
...German	239,299	66.8	47.1	0	100
...French	239,299	26.8	44.3	0	100
...Italian	239,299	6.4	24.4	0	0
Specialization track					
...Biology and chemistry	152,977	19.8	39.9	0	100
...Physics and mathematics	152,977	11.4	31.7	0	100
...Other	152,977	68.8	46.3	0	100
Female HS graduates: college outcomes					
Enrollment within 2yrs					
...at university	137,718	80.9	39.3	0	100
...in STEM	137,718	14.4	35.2	0	100
...in pred. female or balanced STEM	137,718	10	30	0	0
...in pred. male STEM	137,718	4.7	21.2	0	0
STEM bachelor degree within 6yrs	110,327	8.8	28.3	0	0
Male HS graduates: college outcomes					
Enrollment within 2yrs					
...at university	101,581	81.8	38.6	0	100
...in STEM	101,581	33	47	0	100
...in pred. female or balanced STEM	101,581	10.3	30.4	0	100
...in pred. male STEM	101,581	23.1	42.1	0	100
STEM bachelor degree within 6yrs	82,226	21.8	41.3	0	100

Notes: Linked administrative data for all high-school (HS) students graduating between 1999/00 to 2019/20 from the 83 high schools with at least 1 event. Information for specialization tracks is available for students graduating from HS after 2007/08. College outcomes are measured relative to HS graduation year. To measure STEM degrees in college, students graduating from HS after 2015/16 are excluded.

Table 2: 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/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 3: Impact of STEM Events on the Probability of Enrolling and Obtaining a Degree in STEM in College

	Dependent Variable: STEM in college		
	(1)	**(2)**	**(3)**
Outcome	Enrollment	Enrollment for 2yrs	Degree within 6yrs
$Event^{(0)}$	0.954**	1.114***	1.110**
	(0.381)	(0.386)	(0.453)
$Event^{(-20,-2)}$	0.395	0.599	0.350
	(0.389)	(0.413)	(0.401)
$Event^{(1,13)}$	0.262	0.588	0.589
	(0.411)	(0.449)	(0.465)
School FE	Y	Y	Y
Year FE	Y	Y	Y
Mean	22.3	20.4	14.4
N students	239,299	215,745	192,553

* p<.1, ** p<.05, *** p<.01

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). (2) shows the effect of the events on the likelihood of enrolling and staying enrolled in STEM in college for at least 2 years in the 4 years after high-school graduation (sample: graduating cohorts 1999/00-2017/18). (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 1999/00-2014/15). Standard errors adjusted for clustering on the school level are displayed.* p<.1, ** p<.05, *** p<.01

Table 4: 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
Year 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 5: Impact of STEM Events With a High Share of Female Speakers on the Probability of Enrolling in STEM in College, After Controlling for Interactive Presentations

	STEM		**Pred. female STEM**		**Pred. male STEM**	
Model	(1)	(2)	(3)	(4)	(5)	(6)
Tecdays$^{(0)}$	-1.007	-1.712	-1.283**	-1.744**	0.203	-0.023
	(1.014)	(1.184)	(0.607)	(0.701)	(0.722)	(0.807)
Tecdays, high female-speaker share$^{(0)}$	2.725*	1.509	2.614**	1.824**	0.361	-0.033
	(1.417)	(1.29)	(1.021)	(0.844)	(1.01)	(0.961)
Tecdays, high interactive-pres. share$^{(0)}$		2.783**		1.803**		0.911
		(1.247)		(0.881)		(0.884)
School FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Mean	22.3	22.3	10.1	10.1	12.5	12.5
N students	239,299	239,299	239,299	239,299	239,299	239,299

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 a control 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 all not displayed in the table. (1), (3), and (5) present the results when contrasting *Tecdays* to *Tecdays* with a high female-speaker share. (2), (4), and (6) add a measure for *Tecdays* with a high interactive-presentation share. 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 learning 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 student's 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?
- *Learning tools*: Would an objective observer agree with the statement that this presentation uses learning 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 *learning tools*. For active participation, I identify descriptions that mention participation indicators, such as 'asking questions', 'discussions', 'quizzes.' For learning 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 *learning tools*. Thus, 8.6% of presentations identified by ChatGPT as involving active participation may not actually include it (false positives), and approximately one in six presentations involving active participation may be missed (false negatives).

B Appendix Figures



Figure A1: Flyer for *ETH unterwegs*

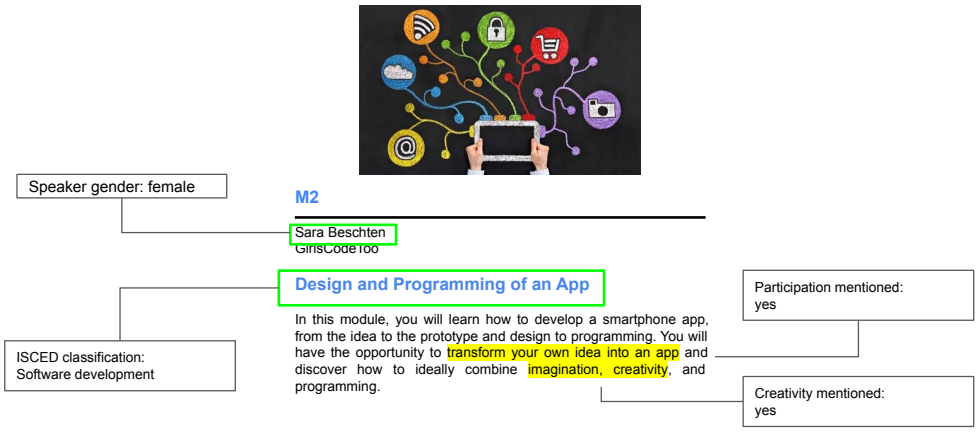


Figure A2: Presentation Description on *Tecdays* flyer

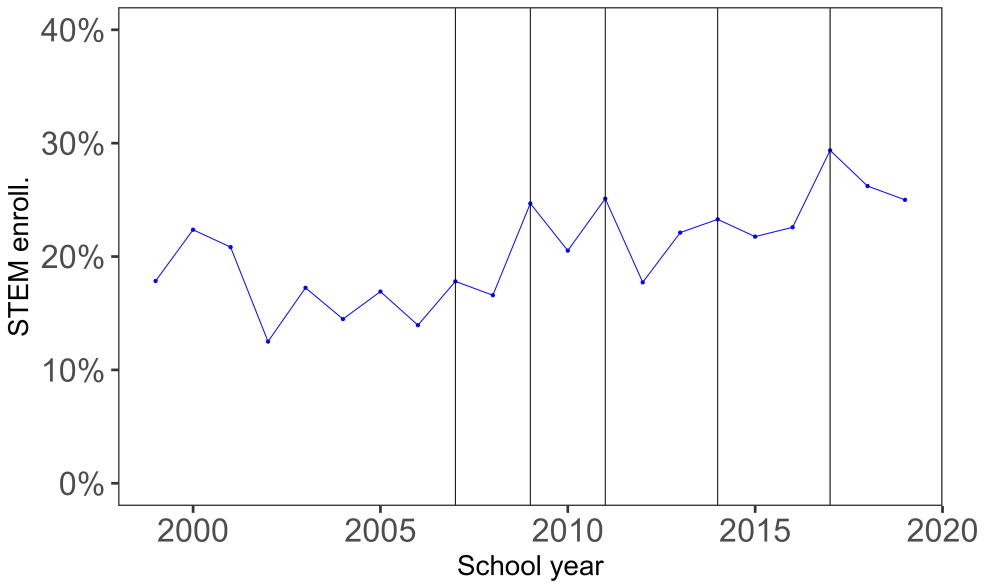


Figure A3: Example: Events and STEM Enrollment in College at a Selected School

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. Vertical lines indicate the years in which events take place at the school.

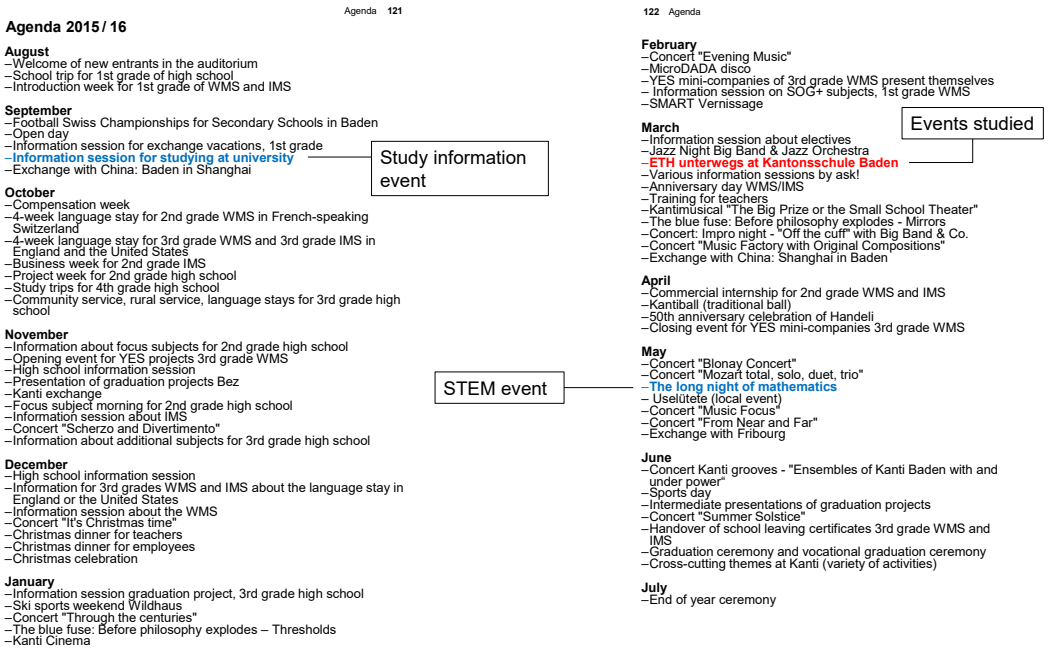


Figure A4: Example: School Calendar

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.

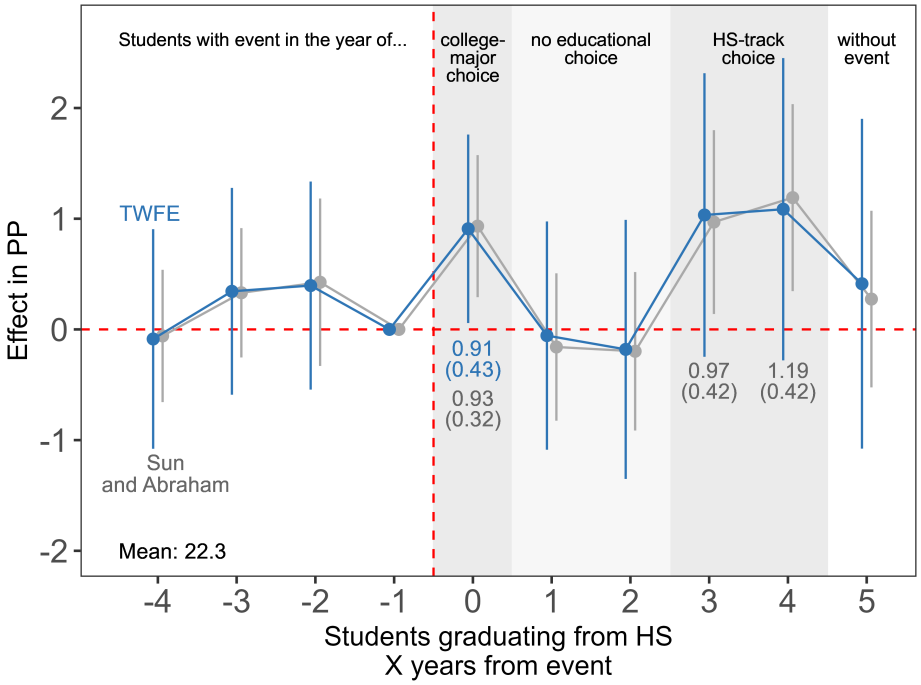


Figure A5: Impact of STEM Events on the Probability of Enrolling in STEM in College

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.

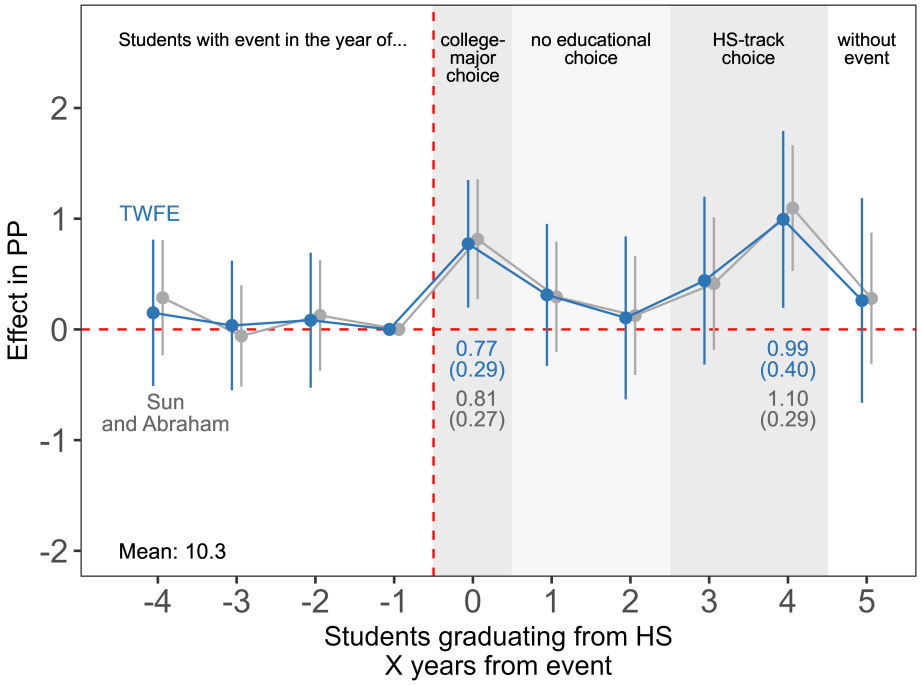


Figure A6: Impact of STEM Events on the Probability of Enrolling in STEM at ETH Zurich

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.

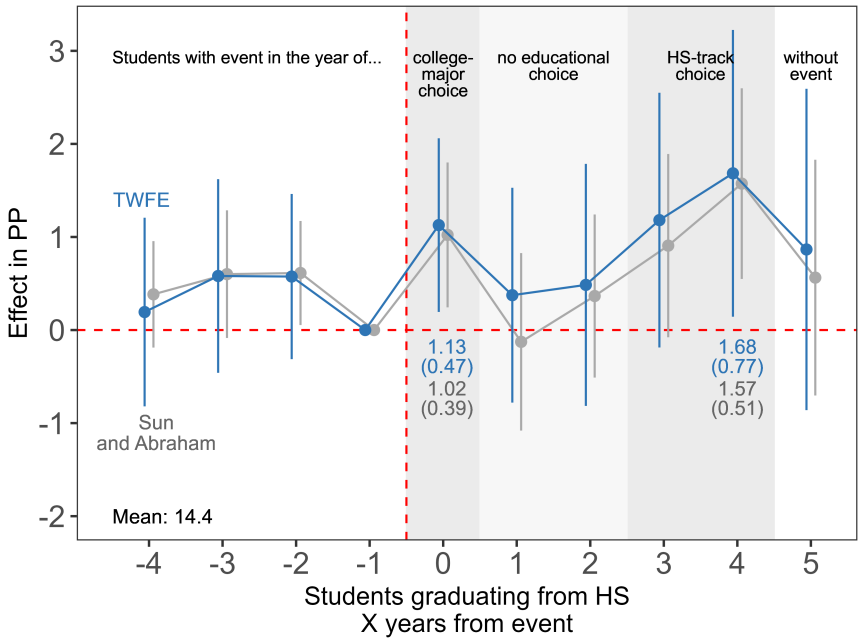


Figure A7: Impact of STEM Events on the Probability of Obtaining a STEM Degree in College

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.

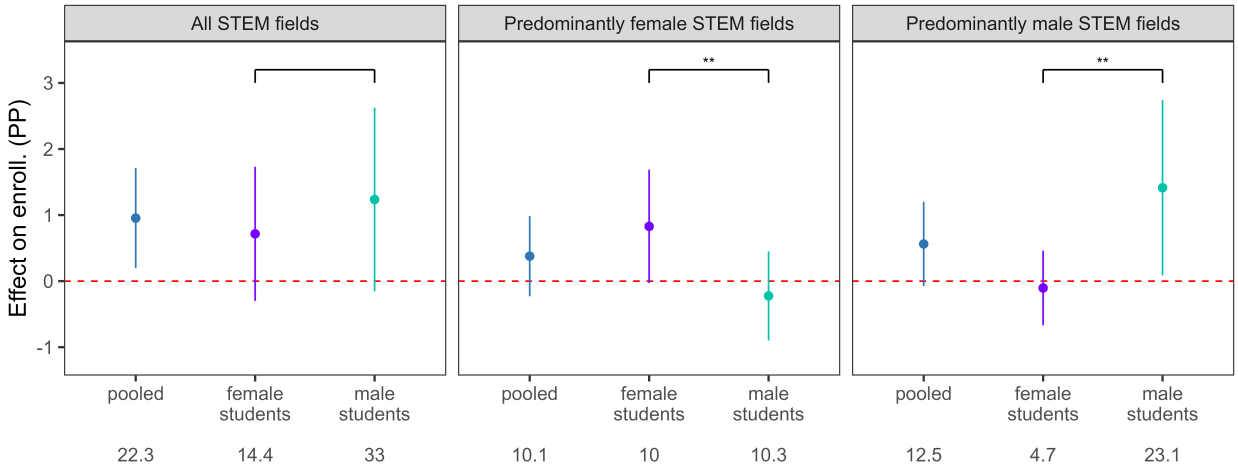
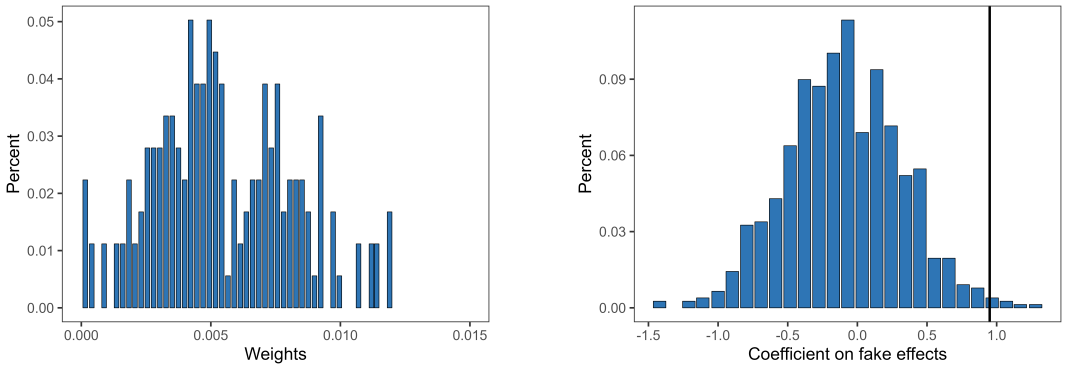


Figure A8: Gender Differences in Event Impact

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.

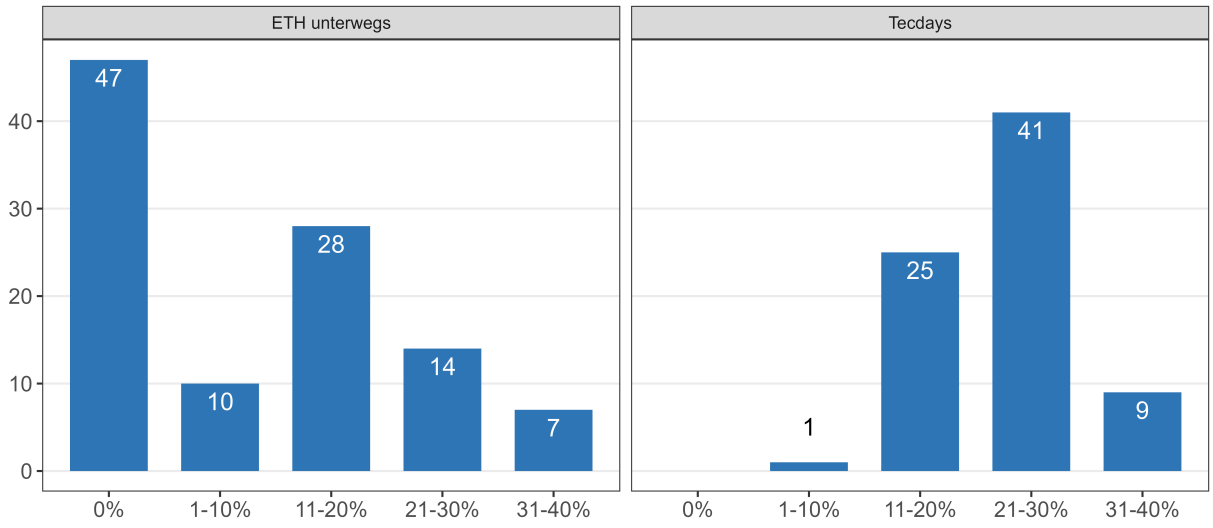


Figure A10: Distribution of Events by Share of Female Speakers

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 0%, *Tecdays* with a high share of female speakers comprise events with a share of female speakers larger than 22%.

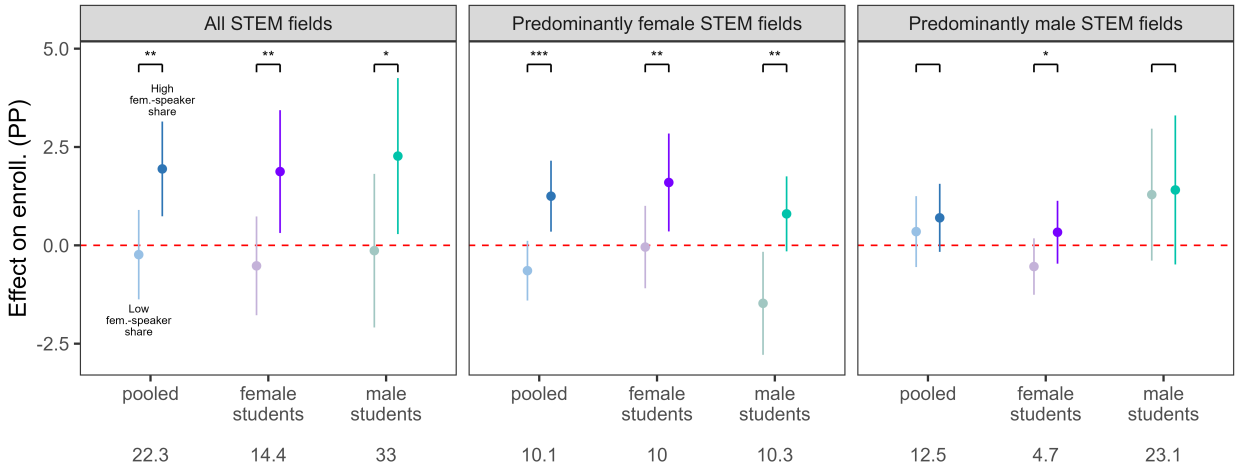


Figure A11: Impact of Event-Level Variation in Female-Speaker Share on STEM Enrollment

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

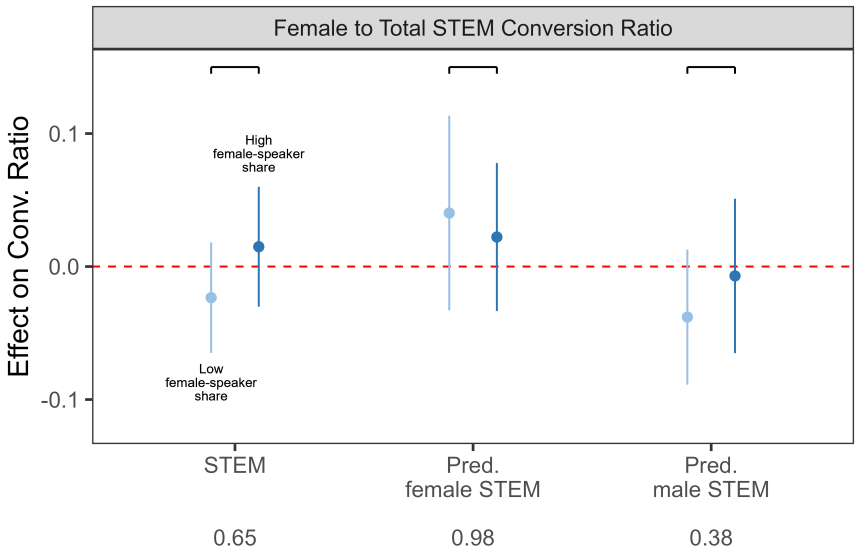


Figure A12: Impact of Event-Level Variation in Female-Speaker Share on the Female to Total STEM Conversion Rate

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 described in equation (4.2): (female HS graduates enrolled in STEM in college / female HS graduates) / (total HS graduates enrolled in STEM in college / total HS graduates). 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

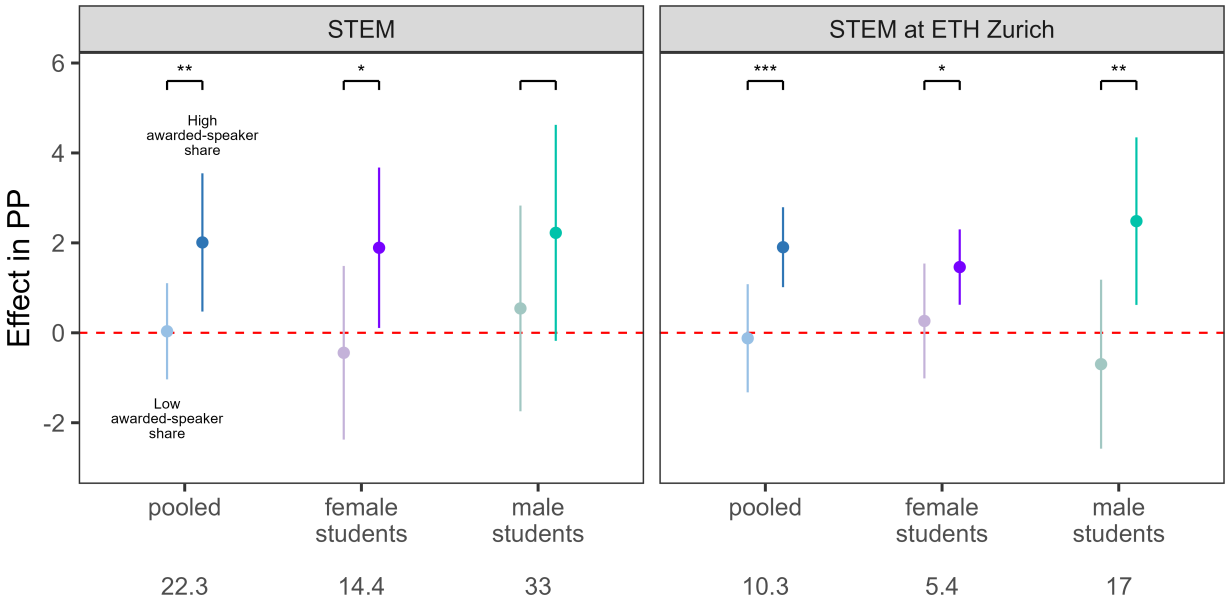


Figure A13: Impact of Event-Level Variation in Speaker Share with Teaching Award on STEM Enrollment

Notes: The figure presents the results for the analysis of changes in speaker composition based on equation (2), exploiting 107 STEM promotion events between 2006 and 2019. The figure shows the effect of an event, depending on its share of speakers who have received a teaching award, on the likelihood that a student enrolls in STEM in college (left) or in STEM at ETH Zurich (right) after graduating from high school. 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

C Appendix Tables

Table A1: 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 A2: 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 A3: 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 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) 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 A4: 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
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 A5: 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
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 A6: 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
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 A7: Balance Table for Female-Speaker Share

	Share of female speakers		
Variable	low	high	coef h
N events	98	85	
N speakers	24.28	30.08	5.807
Month	6.90	6.72	-0.18
Public school	0.99	0.99	-0.002
Any STEM track offered	0.97	0.95	-0.016
N graduates	135.38	144.81	9.425
Share of female graduates	0.56	0.56	-0.002
Language region			
German	0.81	0.75	-0.053
French	0.14	0.16	0.022
Italian	0.05	0.08	0.031
Outcomes in college			
% f enrolling in STEM	11.33	11.60	0.269
% m enrolling in STEM	31.06	31.74	0.676

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. Outcomes in college are calculated based on school years 1999/00 to 2005/06, the years before any event took place. Coef h shows the effect of bivariate regressions on a dummy for events with a high female speaker share. * p<.1, ** p<.05, *** p<.01