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

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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 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.

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1 Introduction

How can we increase female students' enrollment in male-dominated fields, such as STEM? Despite the convergence in gender roles, women remain underrepresented in these fields, with negative implications for innovation and growth (Goldin, 2014; Bertrand, 2020; Hsieh et al., 2019). Drawing on evidence from female political leadership (Beaman et al., 2009, 2012), research shows that female teachers increase female students' participation in traditionally male fields (Card et al., 2022; Carrell et al., 2010). Recent experimental studies demonstrate that even brief interventions with presentations by female experts can positively 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 experts 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, namely *ETH unterwegs* organized by the Swiss Federal Institute of Technology (ETH Zurich) and *Tecdays* by the Swiss Academy of Engineering Sciences. The short events aim to increase students' STEM enrollment in college by exposing high-school students to presentations by STEM professionals. This study draws on data from all 183 events held since 2006, featuring over 4,000 presentations delivered by 351 distinct female speakers and 1,158 male speakers. I link this event data to Swiss administrative data on the study choice and success in college of all 350,000 students who graduated from Swiss high schools between 1999 and 2019.

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 leverage event-level variation in speaker composition to analyze the impact of female speakers in comparison to male speakers.

My preferred event-study specification includes school and year fixed effects and compares STEM participation in college for students graduating from high schools in the years before and after an event, in schools with and without an event. The identification assumption requires that – after controlling for school and 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. Additionally, 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. In the event study, I verify that there are no significant differences in pre-event trends of the outcomes studied.

I find that STEM promotions events increase students' STEM participation. The probability of enrolling in STEM in college increases by 0.95 percentage points (*p-value:* 0.01) for the students who graduate from high school in the year of an event, a 3.8% increase. The impact of the events extends beyond enrollment: leveraging information on students' study success in college, I find that students who have attended an event are 0.89 percentage points (*p-value:* 0.04) more likely to obtain an undergraduate degree in a STEM field within 6 years of high-school graduation, reflecting a 6.4% increase.

The results are robust to potential issues with the two-way fixed effect estimator. I apply the diagnostics by De Chaisemartin and d'Haultfoeuille (2020) to show that none of the weights of my main specification is negative. Following 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 0.91 percentage points, which is very close to my baseline estimate of 0.95. Using a stacked approach as in Cengiz et al. (2019), I demonstrate that my results are robust to using only untreated schools as controls. Finally, I conduct permutation inference and randomly assign events across years in 1,000 replications to show that the reported effects fall outside of the range of placebo effects.

In the second part of my analysis, I exploit event-level variation in speaker composition to investigate whether increasing the share of female speakers reduces the gender gap in students' STEM participation. Event organizers at ETH Zurich and the Academy of Engineering Sciences rely on their network to schedule speakers, and due to speaker availability constraints, the share of female speakers varies across events. I demonstrate that the female-speaker share is not correlated with other observables, such as event size or timing.

I find that events with a high share of female speakers have a significantly larger effect on both female and male students' STEM participation but do not reduce the gender gap in STEM participation. 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, while events with a low female speaker share do not affect STEM enrollment (-0.52 percentage points, *p-value:* 0.41). These effects persist over time, as female students who attend events with a high share of female speakers are more likely to obtain an undergraduate degree in STEM. Similarly, male students are significantly more likely to enroll in STEM after attending events with a high share of female speakers. As a result, I do not find that events with a high share of female speakers reduce the gender gap in STEM enrollment.

Why are female speakers more effective at increasing STEM participation? Previous research often attributes this effect to a role-model mechanism, where female speakers inspire female students, with minimal impact on male students (Beaman et al., 2012; Card et al., 2022). I develop a stylized framework showing that this interpretation assumes that female and male speakers influence students equally through their non-gender traits, such as presentation style. The observed positive effect of female speakers on male students challenges such an assumption and indicates that female speakers may also influence students' beliefs through characteristics that are correlated with speaker gender.

To explore these channels, I first examine whether female and male speakers differ systematically across non-gender traits. I then assess the importance of these traits in influencing students' STEM participation.

I find substantial differences between female and male speakers. Using both administrative data from ETH Zurich and structured information extracted from over 4,000 presentation descriptions, I document that female speakers use a more interactive presentation style, are slightly younger, and are more likely to discuss topics in gender-balanced or predominantly female STEM fields. In contrast, male speakers are more likely to focus on abstract concepts.

I show that the interactive presentation style, more frequently used by female speakers, drives increased STEM participation among both female and male students. First, I find that events with a higher proportion of interactive presentations have a significantly stronger impact on STEM participation. Second, both female and male students are more likely to highlight active participation positively 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 insignificant after controlling for presentation interactivity. No similar effects are found for traits such as speaker age, experience, or topic.

In summary, the results indicate that brief interventions featuring female speakers have a powerful effect on female high-school students' later STEM participation in college, and this positive effect also extends to male students. Both female and male students respond positively to an interactive presentation style, which is more frequent among female speakers. These results suggest that increasing the proportion of female speakers in STEM promotion initiatives can be an effective strategy for boosting overall student participation in STEM. However, involving more female speakers may not substantially narrow the gender gap in STEM enrollment between female and male students.

This paper contributes to the literature in three important ways. First, I document that brief interventions featuring STEM speakers increase STEM graduation rates at scale. Unlike earlier experimental research, I leverage historical observational data across diverse school settings and track long-term effects on educational attainment (Patnaik et al., 2023; Porter and Serra, 2020). While the impact on enrollment aligns with Breda et al. (2023), this study is the first to provide evidence of students' persistence in STEM fields, showing that the events do not result in a mismatch where students are nudged into fields they are unable to complete.

Second, I contribute 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). My analysis shows that female speakers, by employing a more interactive presentation style, communicate about STEM in more effective ways than male speakers, emphasizing the importance of how information is presented. This finding also relates to studies on gender differences in language use, a topic well-documented, for instance, among politicians (Gennaro and Ash, 2022; Dietrich et al., 2019).

Finally, a substantial body of research uses the gender of political leaders, advisors, teachers, or speakers as a proxy for female students' exposure to role models (Card et al., 2022; Bertrand and Duflo, 2017). However, gender may also proxy for differences in how women and men interact with students, as documented in studies on teacher biases (Lavy and Sand, 2018; Carlana, 2019; Terrier, 2020). Similarly, my analysis shows that for brief interventions, the more interactive presentation style, more frequently employed by female speakers, accounts for nearly half of the observed effect of speaker gender.

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. In the last section, I investigate the underlying mechanism for the female-speaker effect.

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 with a potential role model of gender G female F or male M. Beyond their gender G, the potential role models 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 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. Student i therefore possesses subjective beliefs about the payoffs associated with the choice of major j for all $j \in J$. These subjective beliefs take the form of precision weights λ_{ij1} that student i attaches to CL_{ij}. 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 with precision weights λ_{ij0}. I assume that the potential role models can influence students' precision weights 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 j in period 1:

$$U_{ij1} = \begin{cases} (\lambda_{ij0} + \tau_{ijF} + \rho_{ijF})CL_{ij}, & \text{if } T_i = F. \\ (\lambda_{ij0} + \tau_{ijM} + \rho_{ijM})CL_{ij}, & \text{if } T_i = M. \end{cases} \tag{1}$$

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

$$ATE = \underbrace{E[U^1_{ij1}|T_i = F] - E[U^0_{ij1}|T_i = M]}_{\text{effect of being exposed to a f instead of m speaker}} = \underbrace{(\tau_{ijF} - \tau_{ijM})CL_{ij}}_{\text{due to speaker gender}} + \underbrace{(\rho_{ijF} - \rho_{ijM})CL_{ij}}_{\text{due to other channels}} \tag{2}$$

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 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; Canaan and Mouganie, 2023; Breda et al., 2023; Porter and Serra, 2020; Patnaik et al., 2023). This mechanism builds on the observation that female students have lower beliefs than male students in their own ability (self-efficacy) in male-dominated fields. Role incongruity is often emphasized as the source of this gap in beliefs (Bertrand and Duflo, 2017). Exposure to same-gender experts is thought to provide such role models, who can challenge gender stereotypes, thereby improving female students' aspirations and increasing their likelihood of entering traditionally male-dominated fields (Beaman et al., 2012).

Building on this argument and the previously outlined framework, I define 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.

Next, I will discuss three cases to illustrate the assumptions necessary for identifying the role-model mechanism and for female speakers to achieve a reduction in 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

$$\rho_{iT} = 0, \tag{3}$$

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 (3) 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:

$$\rho_{iF} = \rho_{iM}, \tag{4}$$

i.e. female and male experts 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 involving both female and male experts, such as those 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:

$$\rho_{fF} > \rho_{fM}, \quad \rho_{mF} = \rho_{mM}, \tag{5}$$

i.e. female experts have a stronger effect than male experts on female 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 assumptions $\rho_{iT} = 0$, $\rho_{iF} = \rho_{iM}$, and $\rho_{fF} > \rho_{fM}, \quad \rho_{mF} = \rho_{mM}$ are unlikely to hold for the speaker interventions studied. First, I demonstrate that 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 investigate the impact of two events 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. On the day of the event, no classes take place and all students across all grades of a school are expected to attend the presentations. On average, each presentation has a duration of 45 minutes and students attend 6 presentations per event. 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. Each speaker's gender can clearly be infered as all classified names in the sample have a frequency higher than 85% for either being male or female. 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 (LLM) 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 topics relevant to students' experience 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 speaks of issues or phenomena that have been experienced by the students or people in their community? 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 answered the question for yourself and have provided the explanation.

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 show to restrict hallucinations and to improve its accuracy.

Keyword detection To measure gender representation in the presentations, I use keyword detection to identify whether presentations delivered in German mention only generic male or also female occupation titles. I use a list of occupation titles, categorized by their male version ("Ingenieur") and their female version ("Ingenieur*in*").

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 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.

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 A1 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 Analog to the variables measuring STEM enrollment, I create a dummy variable that takes a value of 100 if a high-school students 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 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 year_t, as given by equation (6):

$$\text{Conversion Ratio}^{\text{FT}}{}_{\text{st}} = \frac{(\text{Female HS graduates in STEM in college / Female HS graduates})}{(\text{Total HS graduates in STEM in college / Total HS graduates})} \tag{6}$$

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 $\text{student}_{\text{i}}$ graduating from school_{s} in school year_{t} enrolls or graduates in a STEM study field in college after high school graduation. As my baseline specification, I estimate an event study two-way fixed-effects regression (event study TWFE) of the following specification:

$$Y_{ist} = \gamma Event_{st}^{(-20,-5)} + \sum_{j=-4}^{5} \beta_j Event_{st}^{j} + \delta Event_{st}^{(6,13)} + \mu_s + \theta_t + \epsilon_{ist} \tag{7}$$

where Y_{ist} are the STEM enrollment and graduation outcomes of interest. The events in my setting represent a staggered, non-absorbing treatment, where schools can be treated multiple times. Out of the 142 schools, 59 schools have no event, 30 host one event, and 53 schools have two or more events. For schools hosting multiple events, $Event_{st}^{j}$ is equal to 1 if a student graduates j years from any event and 0 otherwise. $Event^{(-20,-5)}$ and $Event_{st}^{(6,13)}$ are cumulative binned endpoints for all time periods beyond the endpoints (Schmidheiny and Siegloch, 2023). μ_s and θ_t represent school and 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 the years before and after an event, in schools with and without an event.

After tracing out the event effects dynamically, I move to a static two-way fixed-effects regression (static TWFE) of the following form:

$$Y_{ist} = \gamma Event_{st}^{(-20,-2)} + \beta_0 Event_{st}^{0} + \delta Event_{st}^{(1,13)} + \mu_s + \theta_t + \epsilon_{ist} \tag{8}$$

In this specification, my main parameter of interest is β_0 which takes a value of 1 for students who attend an event and graduate in the same year and 0 otherwise. As I control for all graduation cohorts two years before and all cohorts 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 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 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), specifications 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. 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 any other graduation cohort.

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 (7). 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 0.94 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 suggestive evidence of 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 A2 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)[1]. Similarly Table A3 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 education decision. The impact of the events on students who attend an event and graduate 1 to 2 years later is close to zero. This aligns with prior research indicating that information tends to be most effective when delivered at the time of decision-making (Dynarski et al., 2021; Patterson et al., 2019).

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

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.

Moving forward, I focus on the more precisely estimated effect on students who attend an event and graduate in the same year using equation (8).

6.2 Static DiD Results

Table 3, column(1) displays the results from the static TWFE specification in equation (8) 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:* 0.04) more likely to obtain an undergraduate degree in a STEM field, representing a 7.5% 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 A5.

The event series *ETH unterwegs* has a focus on introducing high-school students to the STEM study fields available at ETH Zurich. To further increase confidence in my identification assumption, columns (1) and (2) in Table A4 split aggregated STEM enrollment into STEM at ETH Zurich and STEM at other universities. Reassuringly, I find that the impact of the events is mainly driven by increased STEM enrollment at ETH Zurich (+0.81 percentage points, *p-value:* 0.007).

I then split the sample by student gender and distinguish between predominantly female or gender-balanced STEM fields and predominantly male STEM fields. Figure A6 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 A4, 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 A5 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.

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.

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 A7 shows the distribution of events by female speaker composition. In the regression specification of equation 8, I divide events into events with a low and a high share of female speakers akin to a triple difference estimation. Table A6 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 3 splits the sample by student gender and differentiates between predominantly male and predominantly female or gender-balanced STEM fields. Female students attending events with a high share of female speakers exhibit a 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 (+1.62pp, *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 4 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 4 is the absence of any discernible treatment effect 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 5 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 also 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[2].

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,

[2] The likelihood of receiving an award is slightly lower for female faculty (2.81%) compared to male faculty (3.68%)

on students' likelihood to enroll in STEM fields. Figure 6 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.

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 7, 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.

Finally, 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).

Together, the findings suggest that the influence of female STEM speakers on students' study choices extends beyond role modeling; it encompasses a range of presentation characteristics that resonate with students and drive their interest in STEM fields.

Which other 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 A8 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 events with 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 as good as random 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, wherein female speakers inspire female students solely through shared gender. Instead, the investigation into the underlying mechanisms suggests that the distinct presentation style of female speakers — characterized by interactive engagement — contributes to increased STEM participation among 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 experts in such interventions can enhance their overall effectiveness. However, the results also show that increasing the share of female experts in such interventions is unlikely to reduce the gender gap in STEM enrollment among female and male students.

References

Altonji, J. G. (1993). The demand for and return to education when education outcomes are uncertain. *Journal of Labor Economics*, 11(1, Part 1):48–83.

Altonji, J. G., Arcidiacono, P., and Maurel, A. (2016). The analysis of field choice in college and graduate school: Determinants and wage effects. In *Handbook of the Economics of Education*, volume 5, pages 305–396. Elsevier.

Anelli, M. and Peri, G. (2019). The effects of high school peers' gender on college major, college performance and income. *The Economic Journal*, 129(618):553–602.

Avilova, T. and Goldin, C. (2023). What did uwe do for economics? Technical report, National Bureau of Economic Research.

Baker, A. C., Larcker, D. F., and Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, 144(2):370–395.

Bayer, A., Bruich, G., Chetty, R., and Housiaux, A. (2020). Expanding and diversifying the pool of undergraduates who study economics: Insights from a new introductory course at harvard. *The Journal of Economic Education*, 51(3-4):364–379.

Beaman, L., Chattopadhyay, R., Duflo, E., Pande, R., and Topalova, P. (2009). Powerful women: does exposure reduce bias? *The Quarterly journal of economics*, 124(4):1497–1540.

Beaman, L., Duflo, E., Pande, R., and Topalova, P. (2012). Female leadership raises aspirations and educational attainment for girls: A policy experiment in india. *science*, 335(6068):582–586.

Bertrand, M. (2020). Gender in the twenty-first century. In *AEA Papers and proceedings*, volume 110, pages 1–24. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Bertrand, M. and Duflo, E. (2017). Field experiments on discrimination. *Handbook of economic field experiments*, 1:309–393.

Bleemer, Z. and Zafar, B. (2018). Intended college attendance: Evidence from an experiment on college returns and costs. *Journal of Public Economics*, 157:184–211.

Breda, T., Grenet, J., Monnet, M., and Van Effenterre, C. (2023). How effective are female role models in steering girls towards stem? evidence from french high schools. *The Economic Journal*, 133(653):1773–1809.

Brenøe, A. A. and Zölitz, U. (2020). Exposure to more female peers widens the gender gap in stem participation. *Journal of Labor Economics*, 38(4):1009–1054.

Canaan, S. and Mouganie, P. (2023). The impact of advisor gender on female students' stem enrollment and persistence. *Journal of Human Resources*, 58(2):593–632.

Card, D., Domnisoru, C., Sanders, S. G., Taylor, L., and Udalova, V. (2022). The impact of female teachers on female students' lifetime well-being. Technical report, National Bureau of Economic Research.

Carlana, M. (2019). Implicit stereotypes: Evidence from teachers' gender bias. *The Quarterly Journal of Economics*, 134(3):1163–1224.

Carrell, S. E., Page, M. E., and West, J. E. (2010). Sex and science: How professor gender perpetuates the gender gap. *The Quarterly journal of economics*, 125(3):1101–1144.

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2019). The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics*, 134(3):1405–1454.

Conlon, J. J. (2021). Major malfunction: A field experiment correcting undergraduates' beliefs about salaries. *Journal of Human Resources*, 56(3):922–939.

De Chaisemartin, C. and d'Haultfoeuille, X. (2022). Difference-in-differences estimators of intertemporal treatment effects. Technical report, National Bureau of Economic Research.

De Chaisemartin, C. and d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–2996.

Delfino, A. (2024). Breaking gender barriers: Experimental evidence on men in pink-collar jobs. *American Economic Review*, 114(6):1816–1853.

Dietrich, B. J., Hayes, M., and O'brien, D. Z. (2019). Pitch perfect: Vocal pitch and the emotional intensity of congressional speech. *American Political Science Review*, 113(4):941–962.

Dube, A., Girardi, D., Jorda, O., and Taylor, A. M. (2023). A local projections approach to difference-in-differences event studies. Technical report, National Bureau of Economic Research.

Dynarski, S., Libassi, C., Michelmore, K., and Owen, S. (2021). Closing the gap: The effect of reducing complexity and uncertainty in college pricing on the choices of low-income students. *American Economic Review*, 111(6):1721–1756.

Gennaro, G. and Ash, E. (2022). Emotion and reason in political language. *The Economic Journal*, 132(643):1037–1059.

Goldin, C. (2014). A grand gender convergence: Its last chapter. *American economic review*, 104(4):1091–1119.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277.

Hastings, J., Neilson, C. A., and Zimmerman, S. D. (2015). The effects of earnings disclosure on college enrollment decisions. Technical report, National Bureau of Economic Research.

Hsieh, C.-T., Hurst, E., Jones, C. I., and Klenow, P. J. (2019). The allocation of talent and us economic growth. *Econometrica*, 87(5):1439–1474.

Kirkeboen, L. J., Leuven, E., and Mogstad, M. (2016). Field of study, earnings, and self-selection. *The Quarterly Journal of Economics*, 131(3):1057–1111.

Lavy, V. and Sand, E. (2018). On the origins of gender gaps in human capital: Short-and long-term consequences of teachers' biases. *Journal of Public Economics*, 167:263–279.

Lim, J. and Meer, J. (2017). The impact of teacher–student gender matches: Random assignment evidence from south korea. *Journal of Human Resources*, 52(4):979–997.

OECD (2017). *Getting Skills Right: Skills for Jobs Indicators.*

Patnaik, A., Pauley, G. C., Venator, J., and Wiswall, M. J. (2023). The impacts of same and opposite gender alumni speakers on interest in economics. Technical report, National Bureau of Economic Research.

Patterson, R., Pope, N., and Feudo, A. (2019). Timing is everything: Evidence from college major decisions.

Porter, C. and Serra, D. (2020). Gender differences in the choice of major: The importance of female role models. *American Economic Journal: Applied Economics*, 12(3):226–254.

Schmidheiny, K. and Siegloch, S. (2023). On event studies and distributed-lags in two-way fixed effects models: Identification, equivalence, and generalization. *Journal of Applied Econometrics*, 38(5):695–713.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199.

Terrier, C. (2020). Boys lag behind: How teachers' gender biases affect student achievement. *Economics of Education Review*, 77:101981.

UNESCO (2015). International standard classification of education. fields of education and training 2013 (isced-f 2013)—detailed field descriptions.

Zafar, B. (2013). College major choice and the gender gap. *Journal of Human Resources*, 48(3):545–595.

Figures

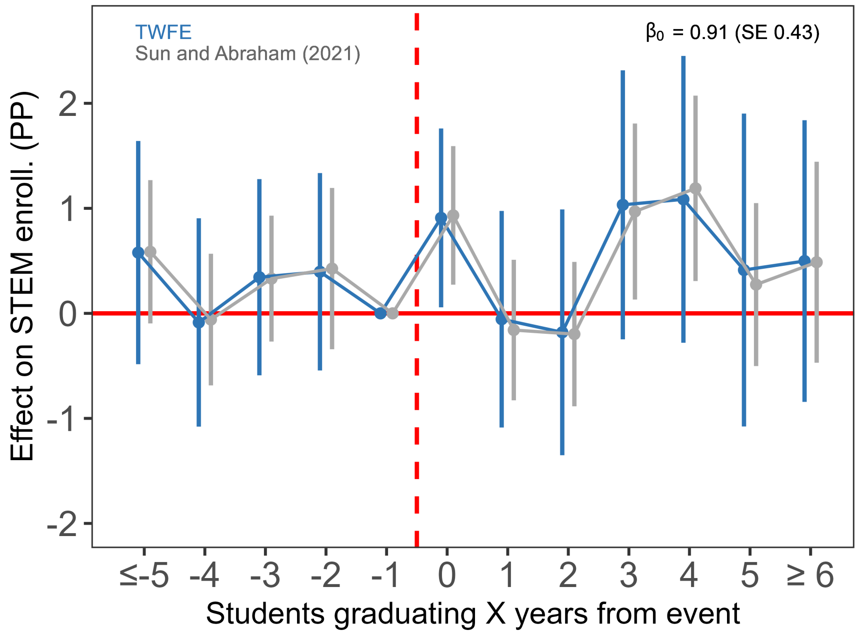


Figure 1: Impact of STEM Events on the Probability of Enrolling in STEM in College

Notes: The figure shows the results from the event study TWFE analysis (blue) as in equation (7), Sun and Abraham (2021) (grey) 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 after graduating from high school. The sample mean is 22.3%. OLS coefficients with the 95% confidence interval (vertical lines) based on standard errors clustered at the school level are displayed. The coefficients in -5 and 6 represent cumulative binned endpoints for all periods before -4 / after 5.

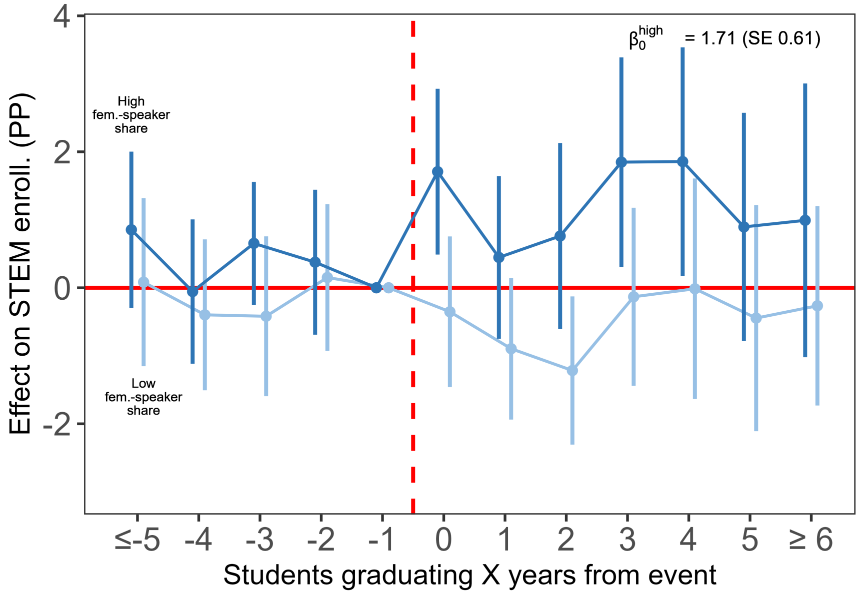


Figure 2: Impact of STEM Events With a High Share of Female Speakers on the Probability of Enrolling in STEM in College

Notes: The figure shows the results from the event study TWFE analysis as in equation (7), 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. The sample mean is 22.3%. OLS coefficients with the 95% confidence interval (vertical lines) based on standard errors clustered at the school level are displayed. The coefficients in -5 and 6 represent cumulative binned endpoints for all periods before -4 / after 5.

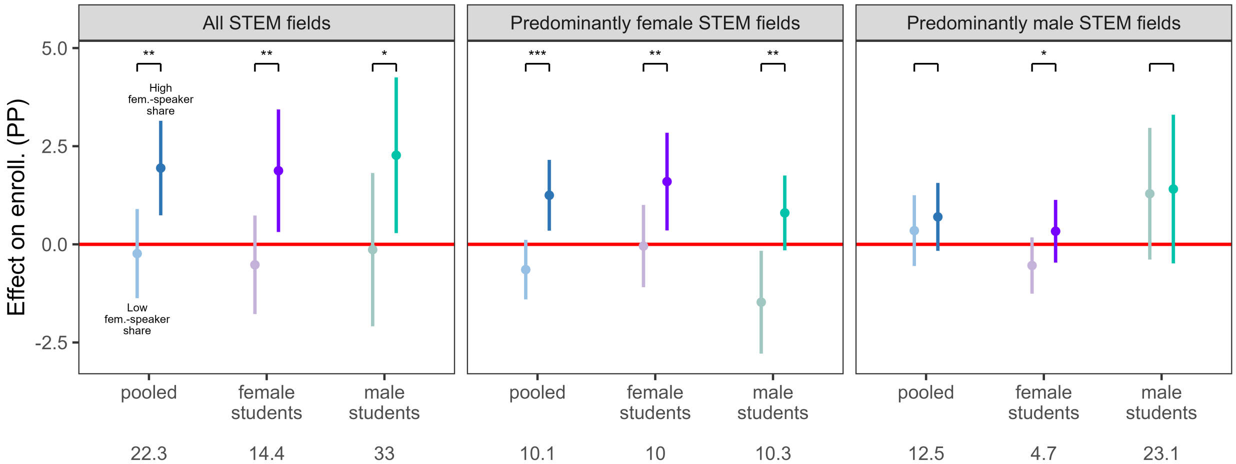


Figure 3: Impact of Event-Level Variation in Female-Speaker Share on STEM Enrollment

Notes: The figure presents the results for the analysis of changes in speaker composition based on equation (8), exploiting 183 STEM promotion events between 2006 and 2019. The figure shows the effect of an event, depending on its female-speaker share, on the likelihood that a student enrolls in STEM in college after graduating from high school. The effect of an event on the students who attend an event and graduate from high school in the same year is shown. STEM is separated into predominantly female or gender-balanced (female share $>$ 40%) and predominantly male fields. OLS coefficients with the 95% confidence interval (vertical lines) based on standard errors clustered at the school level are displayed. Significance levels of differences: * p<.1, ** p<.05, *** p<.01

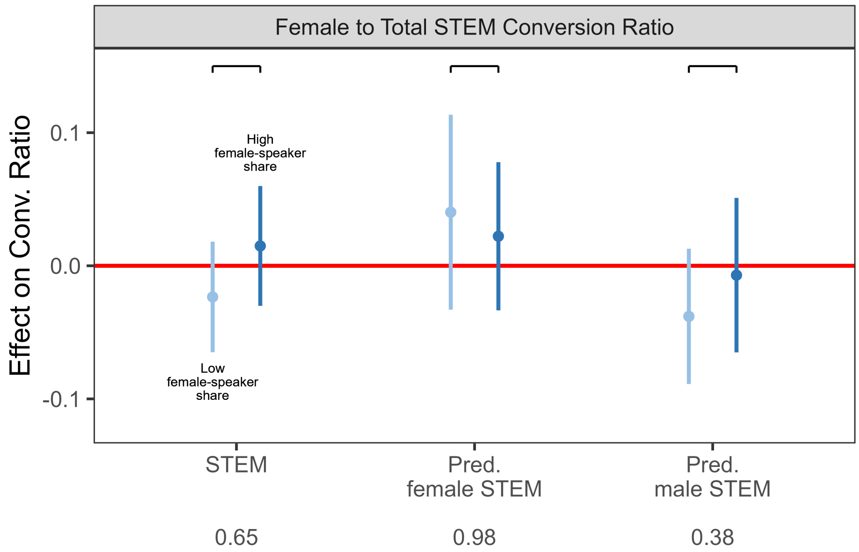


Figure 4: Impact of Event-Level Variation in Female-Speaker Share on the Female to Total STEM Conversion Rate

Notes: The figure presents the results for the analysis of changes in speaker composition based on equation (8), 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 (6): (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

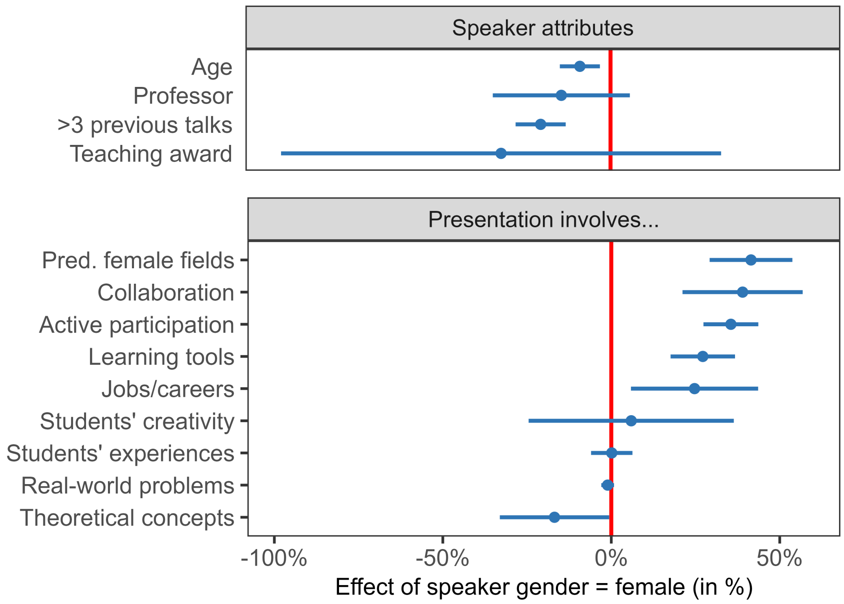


Figure 5: Are There Speaker or Presentation Characteristics Correlated with Female Speakers?

Notes: The figure plots the results from bivariate regressions of speaker and presentations characteristics on a dummy for female speakers, based on data on 4,838 presentations for 107 *ETH unterwegs* and 76 *Tecdays* events between 2006 and 2020. Presentation field and speaking experience is available for both interventions. Age, teaching award, professor title are measured for speakers at *ETH unterwegs* events. Presentation style is available for *Tecdays* events and is based on presentation descriptions. Point estimates and standard errors are standardized by the respective means to allow comparability of effect sizes across regressions.

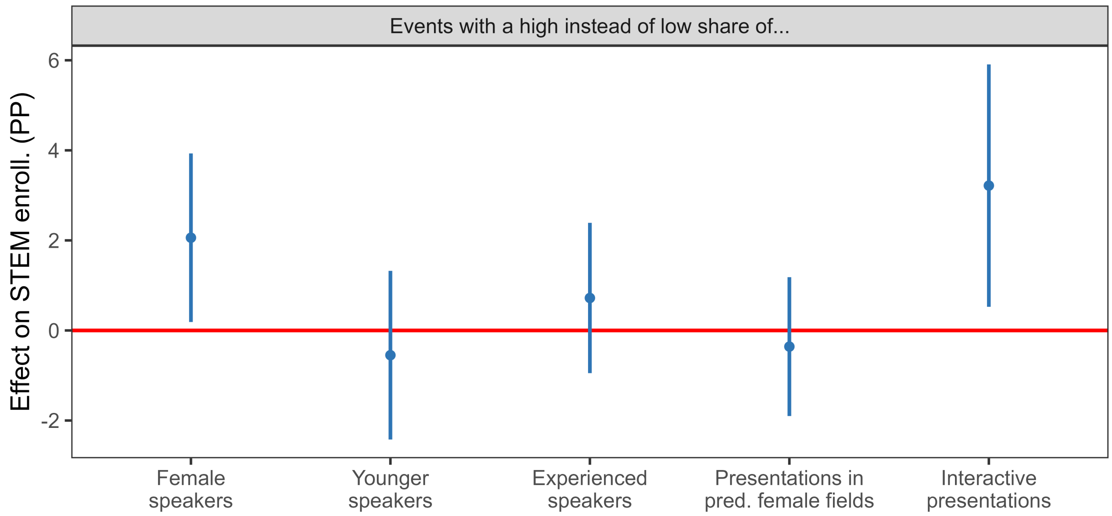


Figure 6: How Do Gender-Correlated Characteristics Impact STEM Participation?

Notes: The figure presents the results for the analysis of changes in speaker and presentation composition based on equation (8), exploiting 183 STEM promotion events between 2006 and 2019. The figure shows the effect of an event with a high share of speakers/presentations in the respective dimension, in comparison to events with a low share, on the likelihood that a student enrolls in STEM in college after graduating from high school. Events with a high share of interactive presentations are defined as the events with a share of presentations involving active participation, students' collaboration, and 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: * $p<.1$, ** $p<.05$, *** $p<.01$

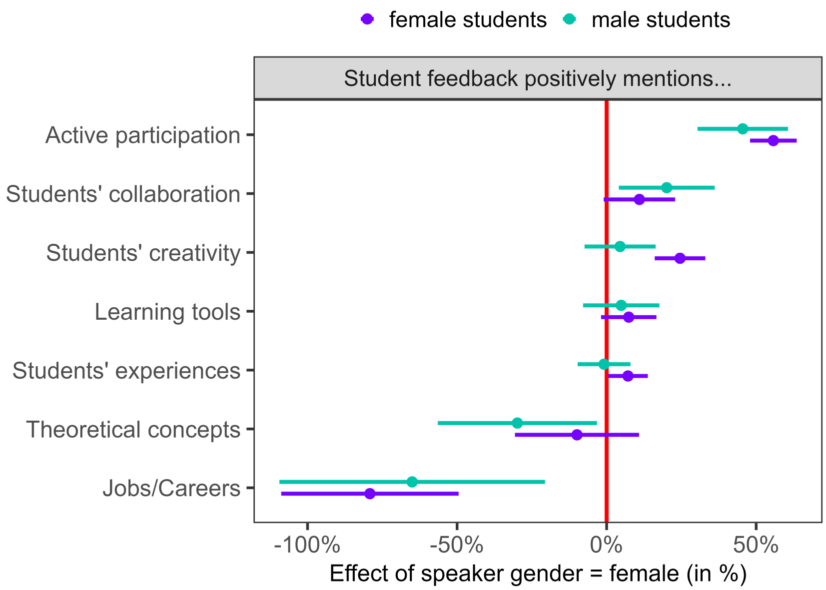


Figure 7: Which Presentation Characteristics Are Students More Likely to Mention in Feedback to Female Instead of Male Speakers?

Notes: The figure presents the results for bivariate regressions of whether a student's presentation feedback mentions a presentation characteristic on a dummy for female speakers. The regressions are based on 38 post-event feedback surveys, comprising 29,775 responses from 9,484 students attending a *Tecdays* event. 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. OLS coefficients with the 95% confidence interval (vertical lines) are displayed.

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 students graduating between 1999/00 to 2019/20 from the 83 high schools with at least 1 event. Information for specialization tracks is available from 2007/08. To measure STEM degrees in college, graduating cohorts 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 (8). All models control for school and 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 (8). All models control for 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 (8). All models control for school and graduation-year fixed effects. (1) represents my baseline specification. (2) combines the estimates for each school with equal weights following 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 (8). 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

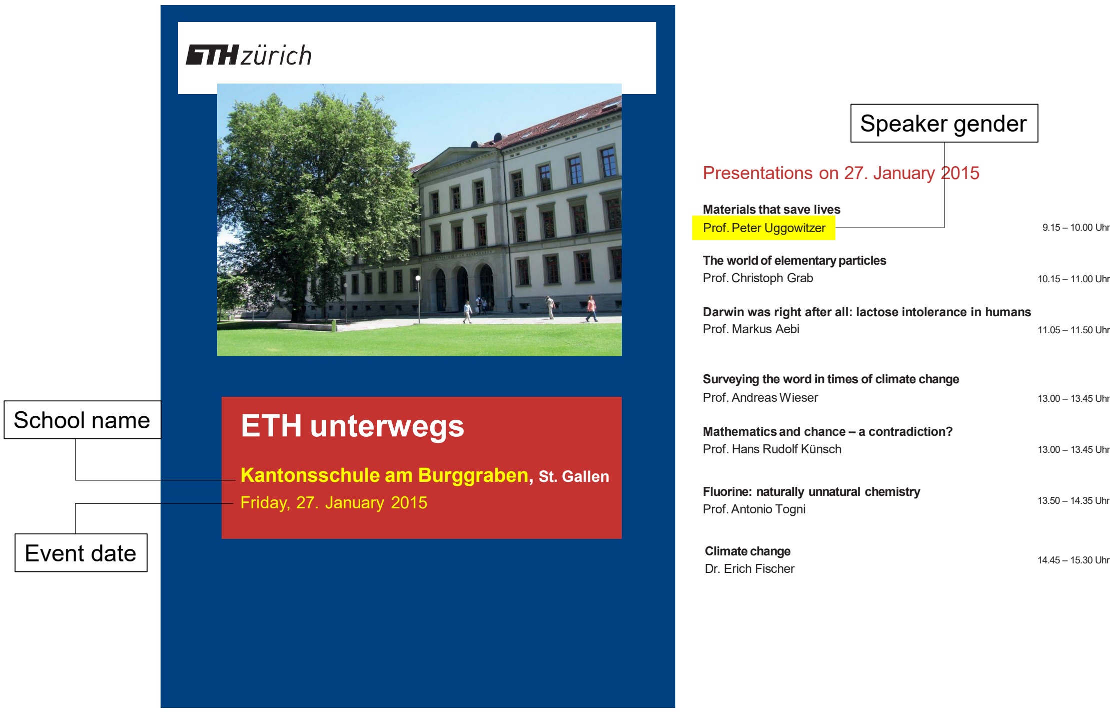


Figure A1: Flyer for *ETH unterwegs*

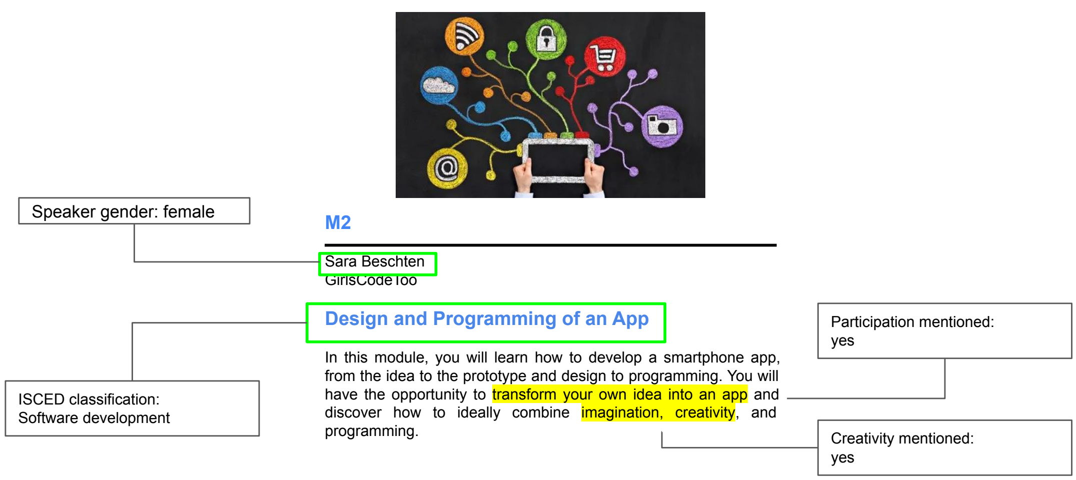


Figure A2: Presentation Description on *Tecdays* flyer

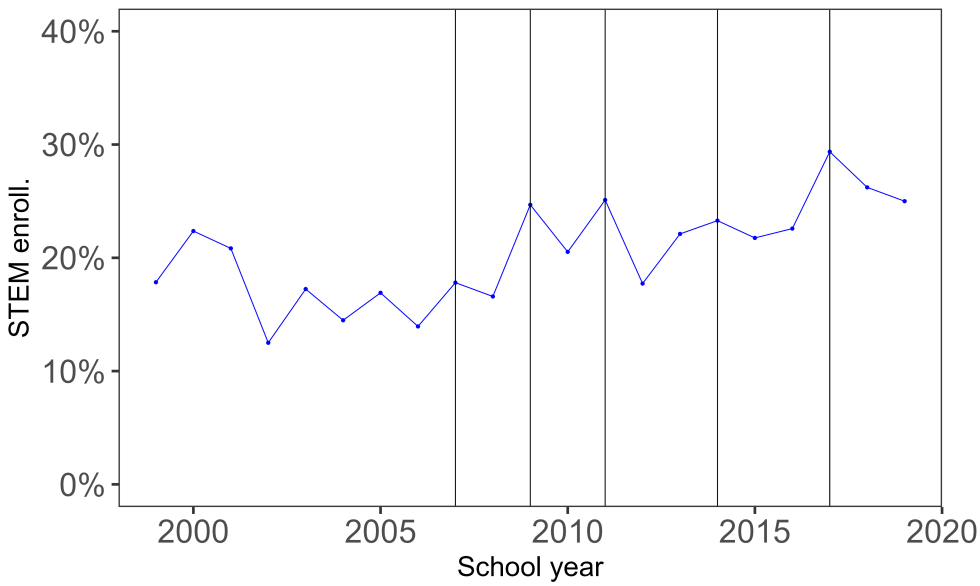
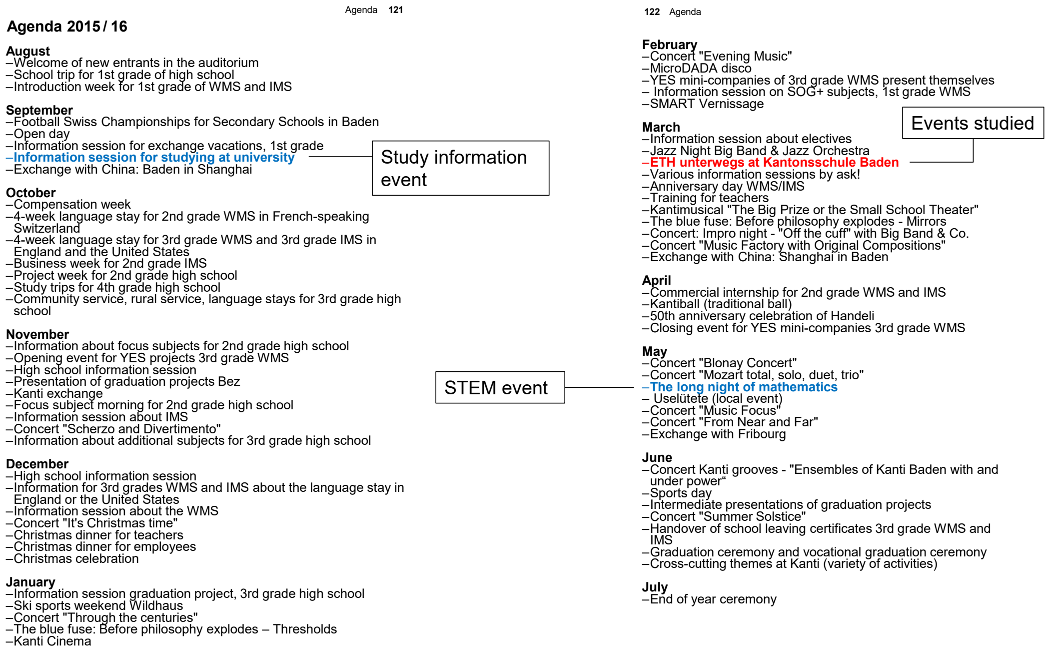


Figure A3: Example: Events and STEM Enrollment in College at a Selected School

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.


Agenda 121

Agenda 2015 / 16

August
–Welcome of new entrants in the auditorium
–School trip for 1st grade of high school
–Introduction week for 1st grade of WMS and IMS

September
–Football Swiss Championships for Secondary Schools in Baden
–Open day
–Information session for exchange vacations, 1st grade
–**Information session for studying at university**
–Exchange with China: Baden in Shanghai

October
–Compensation week
–4-week language stay for 2nd grade WMS in French-speaking Switzerland
–4-week language stay for 3rd grade WMS and 3rd grade IMS in England and the United States
–Business week for 2nd grade IMS
–Project week for 2nd grade high school
–Study trips for 4th grade high school
–Community service, rural service, language stays for 3rd grade high school

November
–Information about focus subjects for 2nd grade high school
–Opening event for YES projects 3rd grade WMS
–High school information session
–Presentation of graduation projects Bez
–Kanti exchange
–Focus subject morning for 2nd grade high school
–Information session about IMS
–Concert "Scherzo and Divertimento"
–Information about additional subjects for 3rd grade high school

December
–High school information session
–Information for 3rd grades WMS and IMS about the language stay in England or the United States
–Information session about the WMS
–Concert "It's Christmas time"
–Christmas dinner for teachers
–Christmas dinner for employees
–Christmas celebration

January
–Information session graduation project, 3rd grade high school
–Ski sports weekend Wildhaus
–Concert "Through the centuries"
–The blue fuse: Before philosophy explodes – Thresholds
–Kanti Cinema

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February
–Concert "Evening Music"
–MicroDADA disco
–YES mini-companies of 3rd grade WMS present themselves
– Information session on SOG+ subjects, 1st grade WMS
–SMART Vernissage

March
–Information session about electives
–Jazz Night Big Band & Jazz Orchestra
–**ETH unterwegs at Kantonsschule Baden**
–Various information sessions by ask!
–Anniversary day WMS/IMS
–Training for teachers
–Kantimusical "The Big Prize or the Small School Theater"
–The blue fuse: Before philosophy explodes - Mirrors
–Concert: Impro night - "Off the cuff" with Big Band & Co.
–Concert "Music Factory with Original Compositions"
–Exchange with China: Shanghai in Baden

April
–Commercial internship for 2nd grade WMS and IMS
–Kantiball (traditional ball)
–50th anniversary celebration of Handeli
–Closing event for YES mini-companies 3rd grade WMS

May
–Concert "Blonay Concert"
–Concert "Mozart total, solo, duet, trio"
–**The long night of mathematics**
– Uselütete (local event)
–Concert "Music Focus"
–Concert "From Near and Far"
–Exchange with Fribourg

June
–Concert Kanti grooves - "Ensembles of Kanti Baden with and under power"
–Sports day
–Intermediate presentations of graduation projects
–Concert "Summer Solstice"
–Handover of school leaving certificates 3rd grade WMS and IMS
–Graduation ceremony and vocational graduation ceremony
–Cross-cutting themes at Kanti (variety of activities)

July
–End of year ceremony

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.

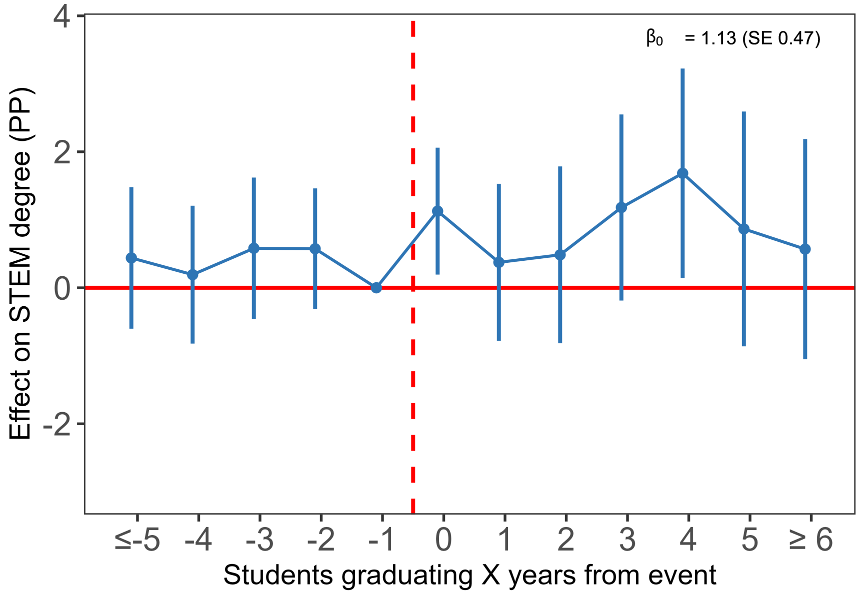


Figure A5: Impact of STEM Events on the Probability of Obtaining a STEM Degree in College

Notes: The figure shows the results from the event study TWFE analysis (blue) as in equation (7), exploiting 183 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. The sample mean is 14.4%. OLS coefficients with the 95% confidence interval (vertical lines) based on standard errors clustered at the school level are displayed. The coefficients in -5 and 6 represent cumulative binned endpoints for all periods before -4 / after 5.

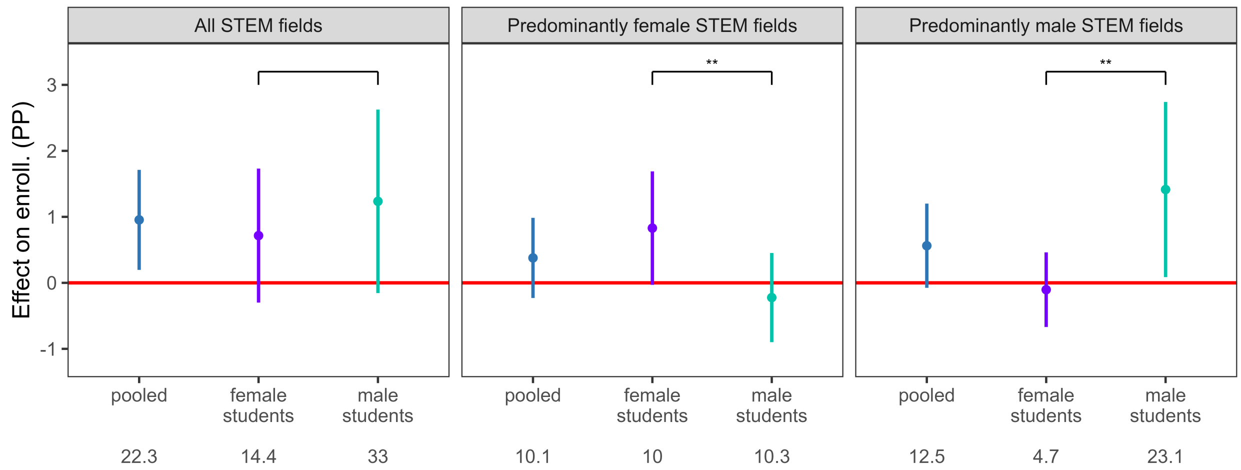


Figure A6: Gender Differences in Event Impact

Notes: The figure shows the results from the static TWFE analysis as in equation (8), 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

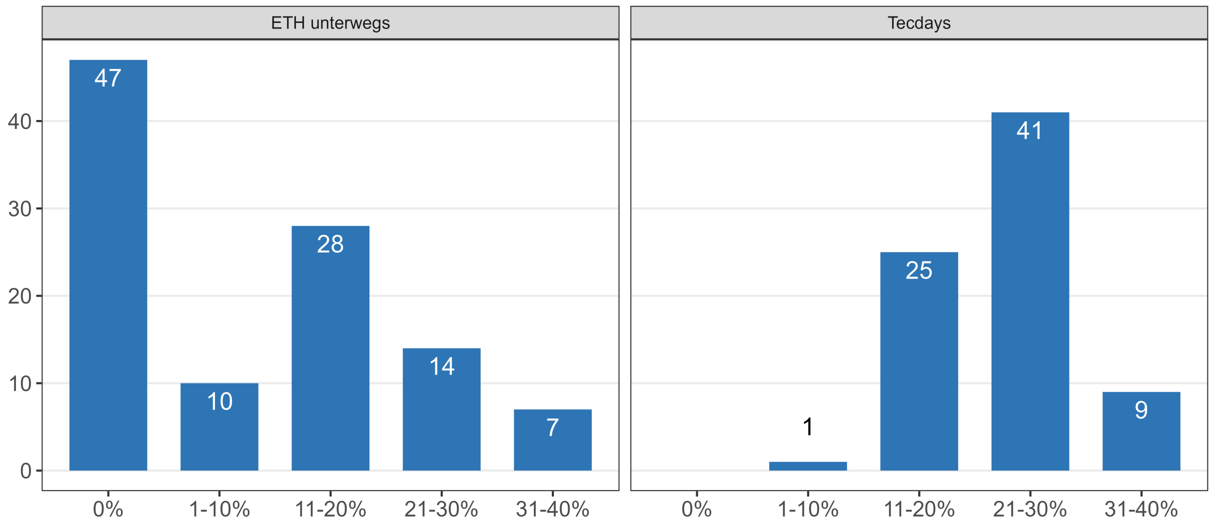


Figure A7: Distribution of Events by Share of Female Speakers

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%.

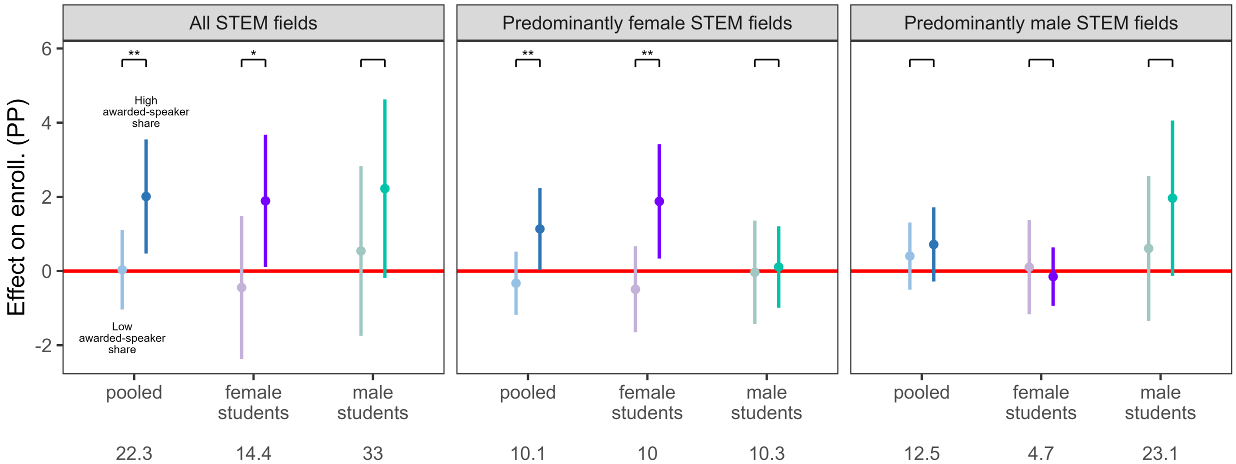
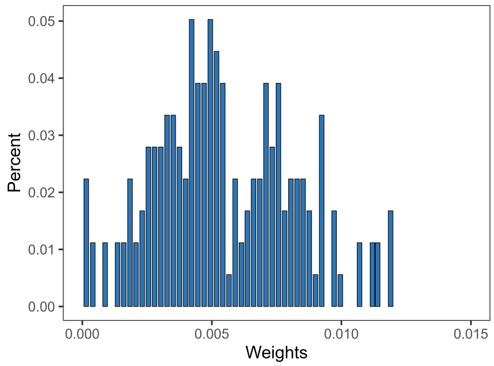
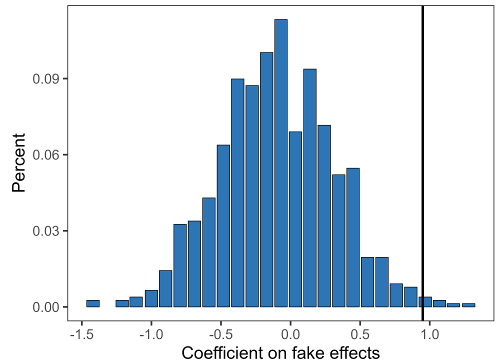


Figure A8: Impact of Event-Level Variation in Speaker Share with Teaching Award on STEM Enrollment

Notes: The figure presents the results for the analysis of changes in speaker composition based on equation (8), 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 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



(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.

Table A1: STEM Study Fields by Gender Mix

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

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

Table A2: Impact of STEM Events on the Probability of Enrolling in a STEM in College by Timing of Track Choice

	Dependent Variable: STEM enrollment in college	
	(1)	**(2)**
Specialization choice	Upon 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 of the static TWFE analysis based on equation (8). All models control for school and graduation-year fixed effects. Model (1) shows the results for students at schools where specialization choice takes place upon entry to the school. Model (2) comprises schools where students select their specialization 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 A3: 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 (8). 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 A4: 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 (8). 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 A5: 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 (8). 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 A6: 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