What Makes a Role Model? STEM Participation and Exposure to Female STEM Experts

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Abstract

I analyze the impact of 183 STEM promotion events in Swiss high schools, involving over 1,500 speakers, on students' educational outcomes. Exploiting students' event exposure in an event-study design, I show that STEM events increase STEM enrollment and graduation at college. Events with a larger share of female speakers result in larger effects for female students, but this positive effect also extends to male students. Investigating the mechanism based on data from 4,000 presentations, I find that female speakers are more likely to focus on predominantly female STEM fields, relate to students' experiences, and encourage active participation in their talks. The findings help inform our understanding of how female speakers increase students' STEM participation.

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1 Introduction

How can we increase female students' enrollment in male-dominated fields, such as economics and STEM? Although the roles of men and women have converged, women continue to make educational choices that translate into lower expected labor market earnings than men (Goldin, 2014; Bertrand, 2020). Starting from the impact of female political leadership (Beaman et al., 2009, 2012), research has shown that female teachers or advisors can increase female students' participation in male-dominated fields (Card et al., 2022; Carrell et al., 2010; Canaan and Mouganie, 2023; Lim and Meer, 2017). Moreover, recent experimental studies have demonstrated that even brief exposure to female speakers affects female students' educational choices (Breda et al., 2023; Porter and Serra, 2020). Even though the common perception is that female teachers or speakers inspire female students as role models in such interactions, the evidence on why exposure to women increases female students' participation in male-dominated fields is limited (Bertrand and Duflo, 2017).

Do female speakers serve as role models to female students because of their gender? Or do they affect students' choices through other characteristics correlated with speaker gender? In this paper, I investigate these questions 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' interest in STEM and expose high-school students to presentations by STEM professionals. I digitize event flyers for all events since the inception of these programs in 2006. In total, I observe 183 events at 83 high schools, featuring over 4,000 presentations delivered by more than 1,500 distinct speakers. I link the event data to Swiss administrative data on the study choice and success of all 350,000 students who graduated from Swiss high schools between 1999 and 2019.

I develop a stylized conceptual framework to formalize how potential role models can influence students' study choices. I define the female role-model effect on female students as the positive impact female potential role models have through their gender on female students' beliefs (in contrast to the impact of their non-gender characteristics). The framework yields two principal insights. First, when comparing the impact of female versus male potential role models, the identification of female role-model effects relies on the assumption that female and male potential role models affect female students' beliefs equally through their non-gender characteristics. Second, the impact of female potential role models on male students' study choices provides a direct test of this assumption as the role of speaker gender for belief updating is likely to be small or negative in this student-speaker match.

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 enrolls or graduates in a STEM study field at college. Subsequently, I exploit event-level variation in speaker composition to analyze the impact of female speakers in comparison to male speakers. My main specification compares STEM enrollment at 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 STEM enrollment in schools with an event and schools without an event would move in parallel in the absence of the event. As school principals reach out to the event organizers to schedule events and thus select their schools into the events, I estimate my main analysis on the schools that schedule at least one event. As a robustness test, I show that my results on this restricted school sample are slightly more conservative than results based on all schools. In the event study, I verify that there are no significant differences in the pretrends of the outcome before an event. Based on the analysis of detailed annual school reports from a sub-sample of schools, I document that schools are also not more likely to organize STEM activities or career events in the years when they host a *Tecday* or *ETH unterwegs* event.

My results show that the probability of enrolling in STEM at 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 at college, I find persistent effects of the events through completion of the undergraduate level. Specifically, 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.

To address potential issues with the two-way fixed effect TWFE estimator, I apply the diagnostics by De Chaisemartin and d'Haultfoeuille (2020) and show that none of the weights of my main event-study 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. I show that my results are robust to using only untreated schools as controls as well as to alternative ways of dealing with potentially longer outcomes dynamics. Finally, I conduct permutation inference and randomly assign STEM events across years in 1,000 replications to demonstrate that the reported effects fall outside of the range of placebo effects.

I then proceed to investigate how effective female speakers are in comparison to male speakers at increasing students' STEM participation. The event organizers reach out to their network when they schedule event speakers. Due to speaker availability constraints, speaker composition varies across events. Exploiting this event-level variation in speaker composition, I show that events with a high share of female speakers have a significantly larger effect on students' STEM participation. Attending an event with a high female speaker share increases students' STEM enrollment – both of female and male students – by 1.90 percentage points (*p-value:* 0.002, +8.52%), while events with a low female speaker share do not have a comparable effect on STEM enrollment (-0.29 percentage points, *p-value:* 0.63, -1.27%). Again these 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. While effects on students' persistence have not been documented in the past, the magnitude of the enrollment effect is comparable to the female-speaker intervention studied by Breda et al. (2023).

What can explain the larger effect that events with a larger female speaker share have on students' STEM participation? To investigate the mechanism, I start by analyzing the effects by student gender and by STEM subfield. My results show that both female and male students are more inclined to enroll in STEM courses after attending events with a larger share of female speakers. These positive effects are particularly pronounced in gender-balanced or predominantly female STEM fields. 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 observed in this paper challenges such an explanation and indicates that female speakers may also influence students' beliefs through other channels.

To explore these channels, I first assess whether speaker quality or experience drives the results. Past interventions have often featured successful women (for e.g. Porter and Serra (2020)). I find suggestive evidence that events with a higher proportion of speakers awarded for teaching excellence have a more substantial impact on STEM enrollment. However, speaker quality does not correlate with speaker gender, nor does speaker experience, measured by the number of presentations delivered at past events.

Next, I examine whether gender differences in presentation topics contribute to the observed effects. While female speakers are more likely to discuss topics in gender-balanced or predominantly female STEM fields, this alone does not fully explain the positive effects of female speakers. When I categorize events by the proportion of presentations in these female-friendly STEM fields, no differential effect on STEM enrollment is observed.

Subsequently, I analyze presentation content and style in greater detail by applying artificial intelligence tools to a unique sample of over 4,000 presentation descriptions. Even after controlling for STEM field, I find that female and male speakers differ significantly in their discourse about STEM. Compared to male speakers, female speakers are more likely to relate to students' personal experiences, emphasize creativity, and encourage active participation during their talks. To investigate the importance of these features for students' STEM participation, I evaluate students' open-ended presentation feedback on what particularly impressed them about each presentation. I find that both female and male students more frequently highlight these features—such as opportunities for active participation and relatability—when providing feedback on presentations delivered by female speakers.

In summary, my results indicate that brief interventions featuring female speakers have a powerful effect on female high-school students' later STEM participation at college, but this positive effect also extends to male students. While speaker quality may play a role independent of speaker gender, the distinct presentation style of female speakers, characterized by relatability, creativity, and interactive engagement, appears to drive the increased STEM participation among both female and male students. Thus, increasing the proportion of female speakers in STEM promotion initiatives proves to 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 advances the literature in three ways. First, I document for the first time that brief interventions with STEM speakers can have long-run impacts on educational outcomes and increase graduation in STEM from college. In contrast to existing work based on field experiments, I analyze interventions with historic observational data that allow tracking such long-run impacts (Porter and Serra, 2020; Breda et al., 2023; Patnaik et al., 2023). Second, I provide new evidence that a short exposure to female speakers has a larger effect on students' STEM enrollment than an exposure to male speakers. Though past studies on long-term exposure find that female versus male teachers increase interest in STEM (Lim and Meer, 2017, 2020; Carrell et al., 2010; Mansour et al., 2022), studies that involve brief exposure to speakers have typically relied exclusively on female speakers (Porter and Serra, 2020; Breda et al., 2023). Finally, I provide new explanations through which female speakers might have a stronger impact on students' educational choices. Previous studies on the effects of teacher gender or speaker interventions have focused mainly on a role-model mechanism (Card et al., 2022; Bertrand and Duflo, 2017). In contrast, this paper highlights that female and male speakers differ in their discourse about STEM and highlights the importance of specific presentation skills and content.

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

2 Conceptual Framework

In this section, I develop a stylized conceptual framework to formalize how exposure to potential role models can influence students' college-major choices. I define what constitutes a female role-model effect, highlight key assumptions required to identify the mechanism, and discuss strategies to investigate the validity of the assumptions. The framework builds on the college-major choice models by Altonji (1993), Altonji et al. (2016) and Zafar (2013) and takes inspiration from Hastings et al. (2015).

2.1 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 or not to any potential role models 0. Beyond their gender G, the potential role models have non-gender characteristics I (e.g. information provided about occupations, communication skills, charisma or stereotypes communicated).

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:

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

2.2 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 $f(I)$. If T_i in (F, M) and 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:

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

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

$$ATE = \Delta U_{ij1} = \begin{cases} E[U^1_{ij1} | T_i = F] - E[U^0_{ij1} | T_i = M] & = (\tau_{ijF} - \tau_{ijM}) CL_{ij} + (\rho_{ijF} - \rho_{ijM}) CL_{ij} \\ E[U^1_{ij1} | T_i = F] - E[U^0_{ij1} | T_i = 0] & = \tau_{ijF} CL_{ij} + \rho_{ijF} CL_{ij} \\ E[U^1_{ij1} | T_i = M] - E[U^0_{ij1} | T_i = 0] & = \tau_{ijM} CL_{ij} + \rho_{ijM} CL_{ij} \end{cases} \tag{2}$$

2.3 Definitions of Female Role Model Effects

Several studies have 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. Exposure to own-gender experts is thought to provide such role models, which can break stereotypes regarding gender roles, and improve individual women's aspirations and propensity to enter traditionally male-dominated areas (Beaman et al., 2012).

Building on this argument and the previously outlined framework, I define two distinct types of female role-model effects on female students. First, focusing on $E[U^1_{fj1}|T_f = F] - E[U^0_{fj1}|T_f = M]$, female student f experiences a *relative* female role model effect if $(\tau_{fjF} - \tau_{fjM})CL_{fj} > 0$, i.e. female student f's beliefs in her outcomes CL_j increase when she is exposed to a female expert instead of a male expert. Second, $E[U^1_{fj1}|T_f = F] - E[U^0_{fj1}|T_f = 0]$ characterizes an *absolute* female role model effect on female students if $\tau_{fjF} CL_{ij} > 0$, implying that female student f experiences a positive change in her beliefs regarding her outcomes $CL_f j$ when exposed to a female expert instead of no expert.

This exercise reveals two important insights. First, studies comparing the effects of exposure to female versus male teachers, advisors, or leaders identify different quantities than studies involving exclusively female experts. Whereas the latter can potentially identify the absolute female role model effect on female students τ_{fjF}, the former is a combination of τ_{fjF} and τ_{fjM}. In this context, the size of the relative female role model effect can be larger than the absolute female role model effect if $\tau_{ijM} < 0$, i.e. if being exposed to a male expert or teacher decreases female students' beliefs in their ability. Second, female role model effects on female students are independent of assumptions regarding the effects of female experts on male students. While studies comparing the effects of exposure to female versus male experts often use the effects on male students to support the existence of a role-model effect, this linkage is conceptually not necessary.

2.4 Identifying Female Role Model Effects

Equation (2) illustrates that random exposure to potential role models can not only shift students' beliefs through expert gender ($\tau_{ijT} = f(G)$) but also through other non-gender expert characteristics ($\rho_{ijT} = f(I)$). Whether we can identify the effects of female role models from $E[U^1_{fj1}|T_f = F] - E[U^0_{fj1}|T_f = M]$ or $E[U^1_{fj1}|T_f = F] - E[U^0_{fj1}|T_f = 0]$ depends on the size of ρ_{ijT}.

If we adopt the assumption

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

i.e. speakers do not affect female students' beliefs through their non-gender characteristics, then $E[U^1_{fj1}|T_f = F] - E[U^0_{fj1}|T_f = M] = (\tau_{fjF} - \tau_{fjM})CL_{fj}$, which represents the specific quantities of interest. This assumption 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.

In contrast, $\rho_{ijF} = 0$ 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 that still allows to identify $(\tau_{fjF} - \tau_{fjM})CL_{fj}$ is:

$$\rho_{fjF} = \rho_{fjM}, \tag{4}$$

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_{ijF} and ρ_{ijM} for relative female role model effects, such as those studied in Card et al. (2022), Carrell et al.

(2010) or Lim and Meer (2017). In contrast, studies on interventions with exclusively female experts such as Porter and Serra (2020) or Breda et al. (2023) rely on $\rho_{ijF} = 0$ to infer the role-model mechanism.

2.5 Testing Assumptions

To gauge the validity of these assumptions, researchers could directly measure ρ_{ijF} and ρ_{ijM} by analyzing how female potential role models interact with students and whether their interaction differs from those of their male counterparts. However, such data is often unavailable (Canaan and Mouganie, 2023).

Instead, studies analyze the effect of female potential role models on male students' educational choices to infer that $\rho_{ijF} = \rho_{ijM}$. Such a strategy implies the assumption that $\tau_{mjF} - \tau_{mjM} = 0$, i.e. female and male experts have the same effect through their gender on male students' beliefs. Adopting this assumption, $E[U^1_{mj1}|T_m = F] - E[U^0_{mj1}|T_m = M]$ simplifies to $(\rho_{mjF} - \rho_{mjM})CL_m$, i.e. the effect of female experts' non-gender characteristics on male students' beliefs relative to male experts' effect. Assuming additionally that $\rho_{fjF} = \rho_{mjF}$, i.e. non-gender characteristics of female experts affect female and male students' beliefs in the same way, it is possible to estimate the size of $(\rho_{fjF} - \rho_{fjM})$. Similarly, when focusing on absolute role model effects, if we assume $\tau_{mjF} = 0$ and $\rho_{fjF} = \rho_{mjF}$, then $E[U^1_{mj1}|T_m = F] - E[U^0_{mj1}|T_m = 0] = \rho_{ijF}CL_{ij}$, a direct measure of the effect of female experts' non-gender characteristics on (male and female) students' beliefs.

In this paper, I present multiple pieces of evidence that assumptions $\rho_{fjT} = 0$ and $\rho_{fjF} = \rho_{fjM}$ are unlikely to hold in brief speaker interventions. First, I show that male students are more likely to enroll in STEM when exposed to events with a larger share of female speakers. This suggests that female speakers affect students' study choices through their non-gender characteristics ($\rho_{ijF} > 0$) and that the effect is larger than the one of male speakers' non gender characteristics ($\rho_{ijF} > \rho_{ijM}$). Second, based on an analysis of short descriptions of around 4000 presentations, I show that female speakers and male speakers differ in the way they deliver their presentations.

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% embark on university 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 at 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.

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-4 Turbo, the latest version available as of writing this study. I follow several techniques recommended by Openai on prompt engineering to optimize the results and enhance reliability. First, I ask the model to adopt a persona. Second, I ask for a concise 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. Column 1 in Table 1 provides an overview of the summary statistics. The data covers college outcomes of all 353,418 students graduating from 142 different schools between

1999/00 and 2019/20. 56.8 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.

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 comprises 21,605 responses from 8,085 students, attending 38 events. 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 $\mathrm{student_i}$ graduating from $\mathrm{school_s}$ in school $\mathrm{year_t}$ enrolls or graduates in a STEM study field at 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:

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

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, D_{st}^{j} is equal to 1 if a student graduates j years from any event and 0 otherwise. $D^{(-20,-5)}$ and $D_{st}^{(6,13)}$ are cumulative binned endpoints for all time periods beyond the endpoints. 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:

$$Y_{ist} = \gamma D_{st}^{(-20,-2)} + \beta_0 D_{st}^{0} + \delta D_{st}^{(1,13)} + \mu_s + \theta_t + \epsilon_{ist} \tag{6}$$

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 identification assumptions. 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. As evidenced in Table 1, schools hosting events indeed differ from schools without events and are more likely to be public institutions, offer a STEM specialization track, and have a higher pre-event share of students pursuing STEM fields post high-school graduation.

To address potential violations of the identification assumptions, I proceed as follows. First, 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 A5 that the results are consistent but slightly more conservative than results based on all 142 schools. Second, I show that schools are not more likely to organize other STEM or study information events in the year when they host 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 A2 shows no effects on the likelihood to organize other STEM activities or host any career or study information events. 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 at 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 at 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 (5). 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 at 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 at 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 A3 in the Appendix, the point estimates on the likelihood of selecting a STEM track in high school and the likelihood of enrolling in STEM at college are positive for students who attend an event shortly before making their high-school specialization choice. In Figure 1, this secondary effect on STEM enrollment at college shows up for students graduating from high school 3 to 4 years after attending an event.[1] However, the point estimates are not statistically significant. Only 34 high schools with events allow students to choose their high-school specialization after entering the school (in the other 49 high schools, students select school and track simultaneously).

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

[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.

(Dynarski et al., 2021; Patterson et al., 2019).

Finally, the effect fades away for students graduating 5 or more years after an event. Given that high school typically lasts 4 years in most schools within the sample, these students have usually not yet been enrolled at the schools and thus have not attended the events. This serves as a placebo test, suggesting that the events are not associated with more fundamental changes in the schools.

Moving forward, I focus on the more precisely estimated effect on students who attend an event and graduate in the same year using equation (6).

6.2 Static DiD Results

Table 2, column(1) displays the results from the static TWFE specification in equation (6) 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 at 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 2, column (3) I present the effect of the events on the likelihood of obtaining an undergraduate degree in STEM at college in the 6 years after high-school graduation. Students who attended an event are 0.89 percentage points (*p-value:* 0.04) more likely to obtain an undergraduate degree in a STEM field, representing a 6.4% 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 at college in the absence of an event.

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 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.

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 A6 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 A5, 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 A5, 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. Notably, 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 A6 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 at 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. In the regression specification of equation 6, 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 speakers 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.

7.2 Mechanisms

In this section, I explore why events with a high share of female speakers increase students' likelihood to enroll in STEM. To investigate the mechanism, I first show that both female and male students are more likely to enroll in STEM after attending events with a high share of female speakers. I then provide evidence that female and male speakers differ in how they deliver their presentations.

I start by replicating the results from the static TWFE specification in equation (6) for the students who graduate in the year of an event. However, this time I split the sample by student gender and distinguish between predominantly female or gender-balanced STEM fields and predominantly male STEM fields. Figure 3 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.

Figure 4 introduces the distinction of events with a low and a high share of female speakers. 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. This effect can be mainly attributed to increased enrollment in predominantly female STEM fields (+1.62pp, *p-value:* 0.01). However, female students are also more likely to enroll in predominantly male STEM subfields. 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.

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 influence students' study choices through distinct non-gender characteristics that may be correlated with speaker gender. In particular, the results presented so far suggest that the impact of female speakers' non-gender characteristics is greater than that of male speakers' non-gender characteristics ($\rho_{ijF} > \rho_{ijM}$). In the following, I investigate such alternative channels.

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 long-term effects of exposure to female teachers or advisors often lack detailed data on student-teacher interactions or advising practices (Canaan and Mouganie, 2023).

I start by investigating the possibility of differential speaker quality or experience across speaker gender. Previous studies on brief interventions featuring female speakers have frequently employed selection criteria beyond speaker gender to select speakers. For instance, Porter and Serra (2020) specifically chose female speakers based on their communication skills and charisma. These additional selection criteria may confound speaker-gender effects.

To measure speaker quality, 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 have received at least one award between 2005 and 2020. Figure **??** 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 larger share of speakers recognized for excellent teaching increase students' STEM enrollment and find suggestive evidence have a larger positive effect on students' STEM enrollment. However, when I analyze the share of awarded speakers by gender, I find that both 20% of female and male speakers have received the award[2]. As an additional measure that likely is correlated with speaker quality, I investigate whether speaker experience – measured as the number of presentations delivered at the events in the past – can explain the female-speaker effect. However, as for the speaker award measure, I find that speaker experience is balanced across speaker gender.

Next, I examine whether gender differences in presentation topics contribute to the observed effects. Both female and male students are more likely to enroll in gender-balanced or predominantly female STEM fields after attending events with a larger share of female speakers. An alternative explanation could be that female speakers more often speak about topics related to these STEM fields. To analyze gender differences in presentation topics, I classify presentations following the International Standard Classification of Education (ISCED) classification system (UNESCO, 2015) based on the presentation title. In total, I classify 4,811 presentations from 119 *ETH unterwegs* and 98 *Tecdays* events between 2006 and 2023. Based on this sample, Figure 5 shows that there are considerable differences in presentation topics between female and male speakers. Female speakers are 10 percentage points (*Tecdays*) or 28.5 percent points (*ETH unterwegs*) more likely to speak about topics related to STEM fields where female students already represent a larger share of students. However, when I categorize events by the proportion of presentations in these female-friendly STEM fields, no differential effect on STEM enrollment is observed. Therefore, differential

[2]The likelihood to receive the award for faculty at ETH in a given year is slightly lower for women (2.81%) and men (3.68%).

presentation topics alone do not fully explain the positive effects of female speakers.

Subsequently, I analyze presentation content and style in more detail by applying artificial intelligence tools to a unique sample of presentation descriptions, covering 4,307 presentations by 1,011 speakers across all 83 *Tecdays*. I use the Large Language Model ChatGPT to extract structured information from the presentation descriptions. Section 4 describes the text classification in more detail.

Table 3 shows that there are substantial differences in content between female and male speakers. Specifically, female speakers exhibit a significantly greater likelihood than their male counterparts to encourage student's participation in their presentations. Additionally, they are twice as likely to employ gender-sensitive occupational titles. Moreover, I observe that female speakers are more inclined to motivate their presentations by referencing students' everyday lives, to incorporate references to creativity, and to actively engage with students through the utilization of films, exhibits, or experiments. This pattern holds even after controlling for presentation topic.

I provide evidence indicating that these presentation features can influence students' STEM enrollment. Using the Large Language Model ChatGPT, I extract structured information from post-event feedback surveys administered by the Swiss Academy of Engineering Sciences. Table 4 presents the results. Notably, both female and male students are significantly more likely to positively highlight these features in their feedback on presentations by female speakers compared to male speakers. For example, 42% of students mentioned being particularly impressed with the opportunity to participate during presentations delivered by female speakers, whereas only 32% mentioned interactivity positively for presentations by male 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 at 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 mechanism suggests that the distinct presentation style of female speakers — characterized by relatability, interactive engagement, and a focus on creativity — drives 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 at 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.

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Tables

Table 1: Summary Statistics

Variable	All schools	Schools with: no event	Schools with: event	Coef treated
N schools	142	59	83	
N unique graduates	353,418	114,119	239,299	
School-level variables				
N graduates per year	120.75	95.97	138.36	42.396***
Share of female graduates	56.85	55.12	58.08	2.958*
Public school	90.14	77.97	98.80	20.829***
Any STEM high-school track offered	83.80	66.10	96.39	30.284***
Language region				
German	71.13	69.49	72.29	2.798
French	24.65	28.81	21.69	-7.127
Italian	4.23	1.69	6.02	4.329
Outcomes at college				
% male graduates enrolling in STEM	27.59	23.92	30.20	6.282***
% female graduates enrolling in STEM	10.47	9.57	11.11	1.549**
% male graduates obtaining STEM degree	11.43	8.89	13.23	4.337***
% female graduates obtaining STEM degree	4.56	3.62	5.23	1.607***

Notes: The table shows the summary statistics for the administrative data, aggregated by school. Columns 3 and 4 split the schools by treatment status. Column Coef treated shows the effect of bivariate regressions on a dummy that indicates whether a school hosts at least 1 event. Outcomes at college are calculated based on school years 1999/00 to 2005/06, the years before any event took place. * p<.1, ** p<.05, *** p<.01

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

	DV: STEM at college		
	(1)	**(2)**	**(3)**
Outcome	Base	Enrollment for 2yrs	Degree
$D^{(0)}$	0.954**	1.114***	0.897**
	(0.381)	(0.386)	(0.431)
$D^{(-20,-2)}$	0.395	0.599	0.261
	(0.389)	(0.413)	(0.372)
$D^{(1,13)}$	0.262	0.588	0.295
	(0.411)	(0.449)	(0.426)
Mean	22.3	20.4	14.1
N students	239,299	215,745	203,838

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

Notes: The table shows the point estimates of the static TWFE analysis based on equation (6). 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 at 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 at college in the 6 years after high-school graduation (sample: graduating cohorts 1999/00-2015/16). Standard errors adjusted for clustering on the school level are displayed.* p<.1, ** p<.05, *** p<.01

Table 3: How do Female and Male Speakers Talk About STEM?

	female experts		male experts		mixed		
Variable	n	freq	n	freq	n	freq	coef f
Presentation refers to...							
students' personal experiences	834	0.71	3,122	0.64	351	0.60	0.062*
students' creativity	834	0.16	3,122	0.11	351	0.12	0.066**
specific careers	834	0.49	3,122	0.54	351	0.73	-0.041
male occupation titles	562	0.20	2,226	0.23	217	0.18	0.011
gender-sensitive occupation titles	562	0.12	2,226	0.06	217	0.07	0.08*
Presentation style							
Involves active participation	834	0.71	3,122	0.45	351	0.66	0.218***
Uses supportive learning tools	834	0.61	3,122	0.45	351	0.58	0.131***
Encourages collaboration	834	0.43	3,122	0.32	351	0.45	0.13***

Notes: The table shows descriptive statistics for 4,307 presentations delivered by 1,011 speakers across 83 *Tecdays* events. I classify the texts using ChatGPT and keyword extraction as described in Section 4. Coef f shows the effect of bivariate regressions on a dummy for female speakers, after controlling for STEM subfields. * p<.1, ** p<.05, *** p<.01

Table 4: What Impresses Students About the Presentations?

	female experts		**male experts**		**mixed**		
Variable	n	freq	n	freq	n	freq	coef f
I was impressed how the presentation...							
Involves active participation	4,534	0.42	14,455	0.32	1,846	0.49	0.08***
Relates to students' experiences	4,534	0.47	14,455	0.41	1,846	0.47	0.043***
Requires students' creativity	4,534	0.06	14,455	0.04	1,846	0.06	0.025**
Uses supportive learning tools	4,534	0.23	14,455	0.20	1,846	0.21	0.017**

Notes: The table shows descriptive statistics for 38 post-event feedback surveys, comprising 21,605 responses from 8,085 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. Coef f shows the effect of bivariate regressions on a dummy for female speakers, after controlling for STEM subfields. * $p<.1$, ** $p<.05$, *** $p<.01$

Figures

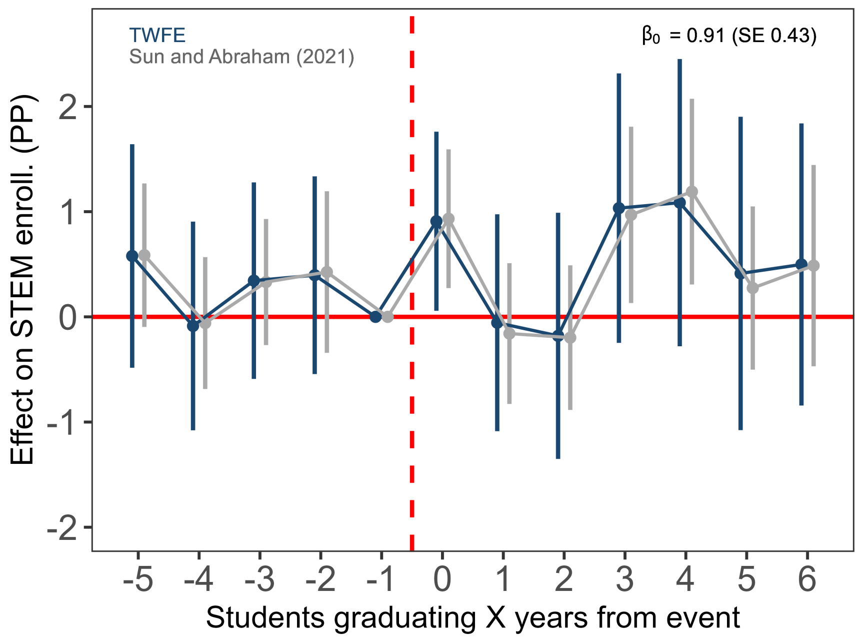


Figure 1: Impact of STEM Events on the Probability of Enrolling in STEM at College

Notes: The figure shows the results from the event study TWFE analysis (blue) as in equation (5), exploiting 183 STEM promotion events between 2006 and 2019. The figure shows the effect of an event on the likelihood that a student enrolls in STEM at 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 leads/lags for all periods before -4 / after 5. Sun and Abraham (2021) combines the estimates for each school with equal weights.

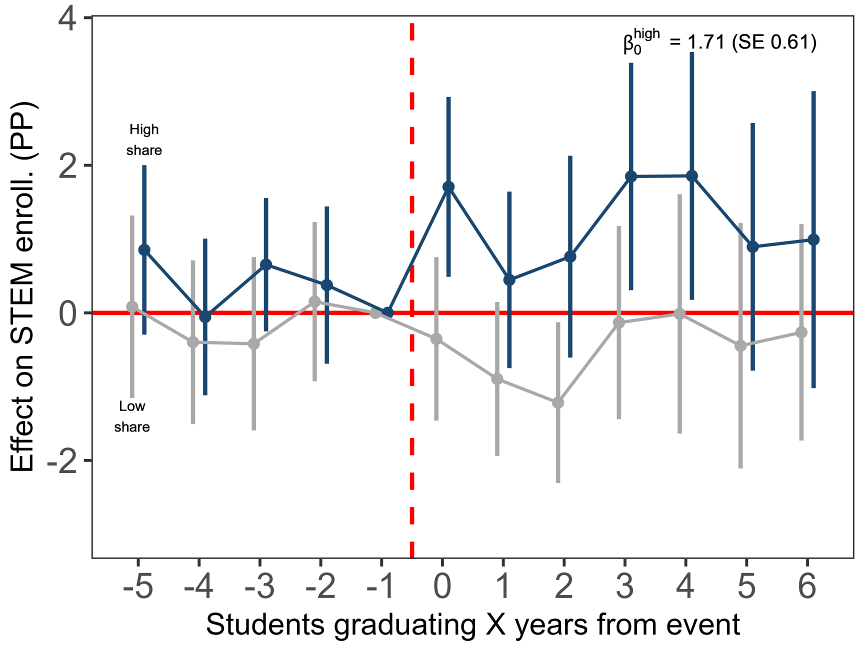


Figure 2: Impact of STEM Events With a High Share of Female Speakers on the Probability of Enrolling in STEM at College

Notes: The figure shows the results from the event study TWFE analysis as in equation (5), 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 (grey) of female speakers on the likelihood that a student enrolls in STEM at 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 leads/lags for all periods before -4 / after 5.

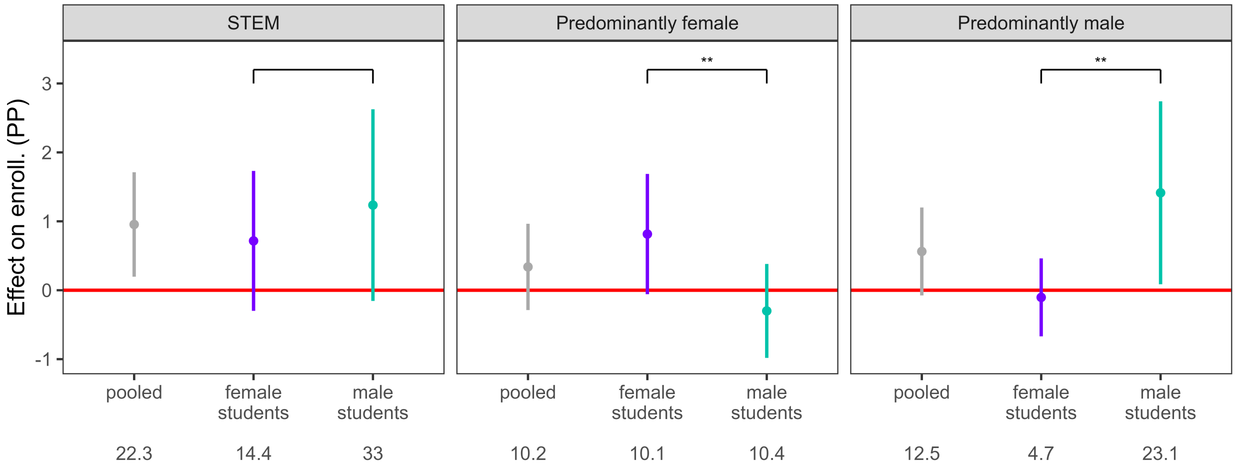


Figure 3: Gender Differences in Event Impact

Notes: The figure shows the results from the static TWFE analysis as in equation (6), exploiting 183 STEM promotion events between 2006 and 2019. The figure shows the effect of an event on the likelihood that a student enrolls in STEM at 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

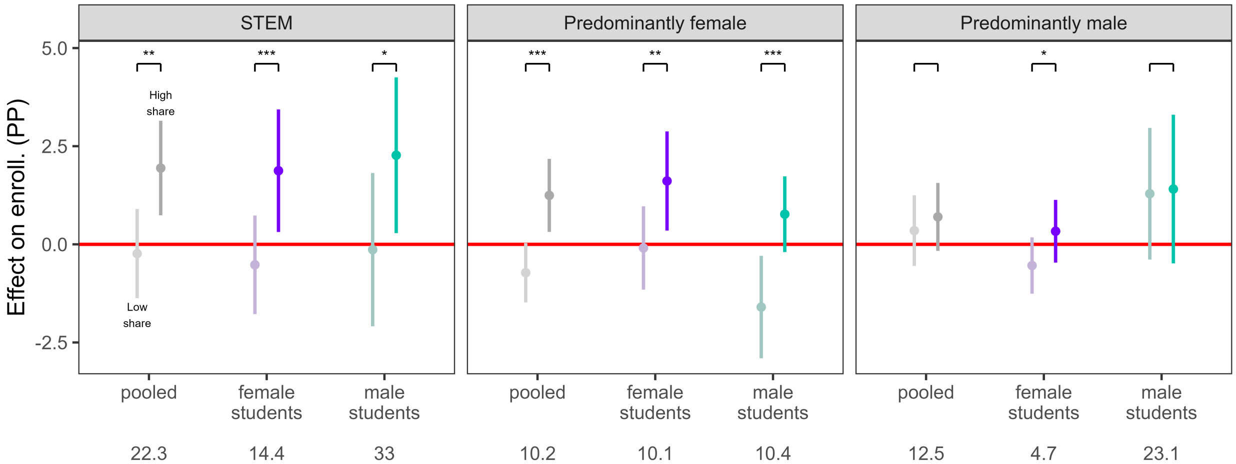


Figure 4: Impact of Event-Level Variation in Female-Speaker Share on STEM Enrollment

Notes: The figure presents the results for the analysis of changes in speaker composition based on equation (6), 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 at college after graduating from high school. 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

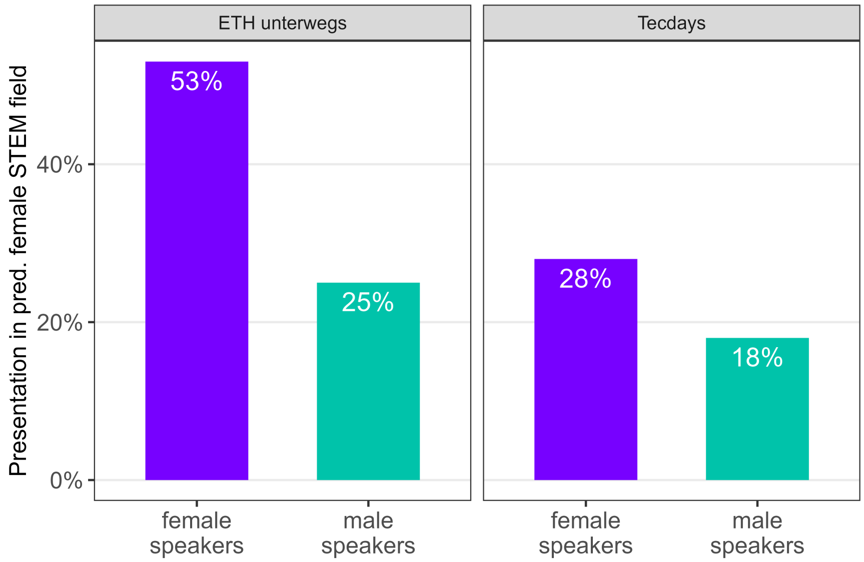


Figure 5: Female Speakers are More Likely to Cover Topics in Predominantly Female or Gender-Balanced STEM Fields

Notes: The figure plots the likelihood that a presentation is delivered in a predominantly female or gender-balanced STEM subfield, based on data on 4,811 presentations for 119 *ETH unterwegs* and 98 *Tecdays* events between 2006 and 2023. Presentations are classified following the International Standard Classification of Education (ISCED). STEM fields are separated into predominantly female or gender-balanced (female share $>$ 40%) and predominantly male fields.

Appendix

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

	Annual school calendar mentions ...					
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	Tecday / ETH unt.	STEM presentation	STEM event	STEM study week	Career event	Study event
D_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)
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 (6). 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. D_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 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 at college
$D^{(0)}$	1.011	0.849	0.162	1.076
	(0.685)	(0.668)	(0.529)	(0.867)
$D^{(-12,-2)}$	0.457	0.338	0.119	-0.37
	(0.631)	(0.659)	(0.317)	(0.582)
$D^{(1,12)}$	0.248	-0.003	0.251	0.368
	(0.906)	(0.787)	(0.45)	(0.777)
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 (6). 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. $D^{(0)}$ 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 at 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)
$D^{(0)}$	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)
$D^{(-20,-2)}$	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)
$D^{(1,13)}$	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)
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 (6). All models control for school and graduation-year fixed effects. The sample are 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: Robustness of Results to Alternative Specifications

	DV: STEM enrollment at college						
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$D^{(0)}$	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)
$D^{(-20,-2)}$	0.395	0.344	0.393	0.082	0.333		0.228
	(0.389)	(0.406)	(0.362)	(0.314)	(0.349)		(0.30)
$D^{(1,13)}$	0.262	0.799	0.492	0.281	0.417		
	(0.411)	(0.493)	(0.396)	(0.371)	(0.457)		
$D^{(5,13)}$							0.095
							(0.399)
Specification	Baseline	Equal weights	All schools	Stacked, clean controls	School trends	Simple DiD	Treated control
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 (6). 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 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 at 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 at 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

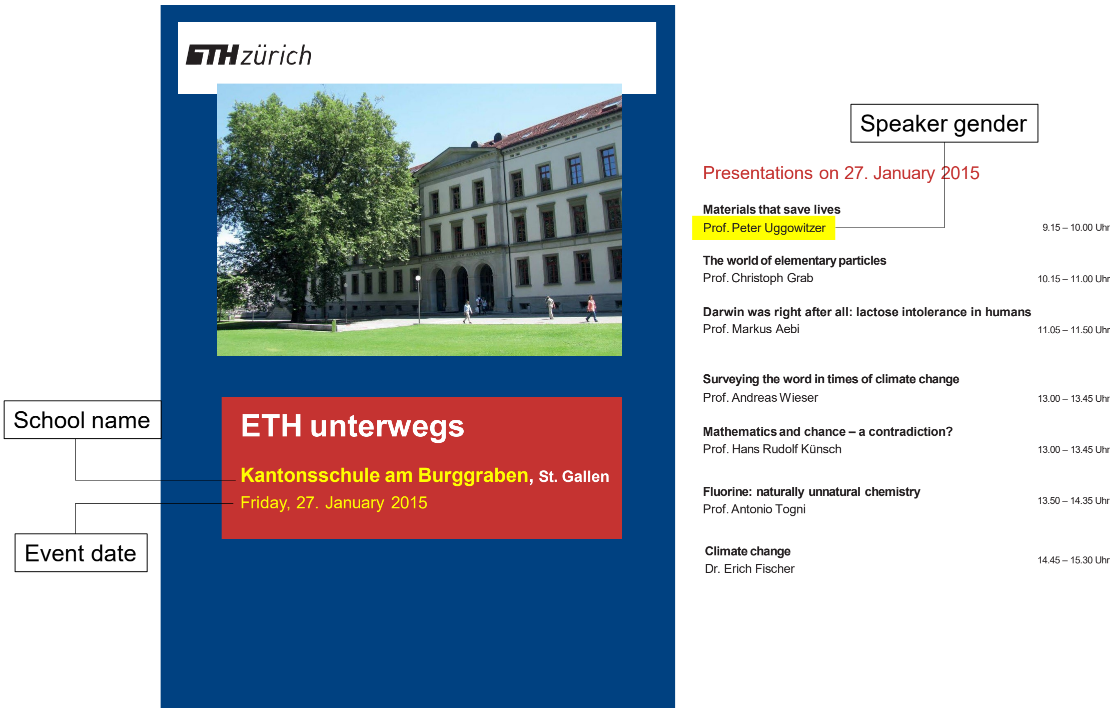


Figure A1: Flyer for *ETH unterwegs*

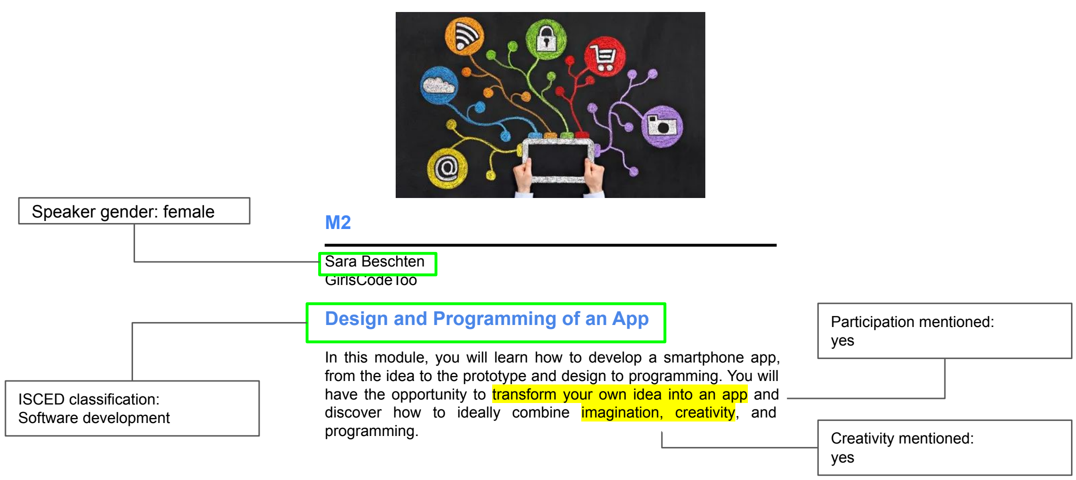


Figure A2: Presentation Description on *Tecdays* flyer

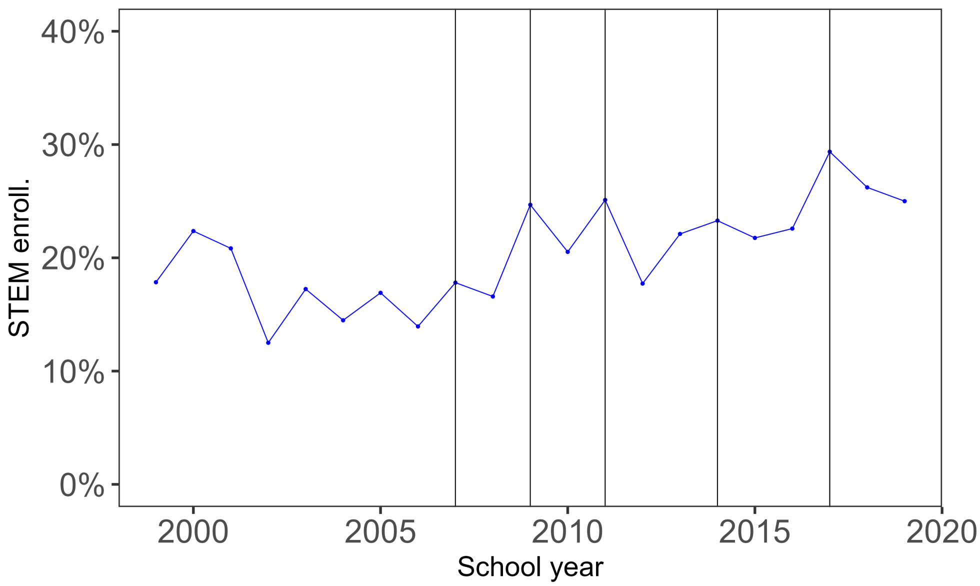
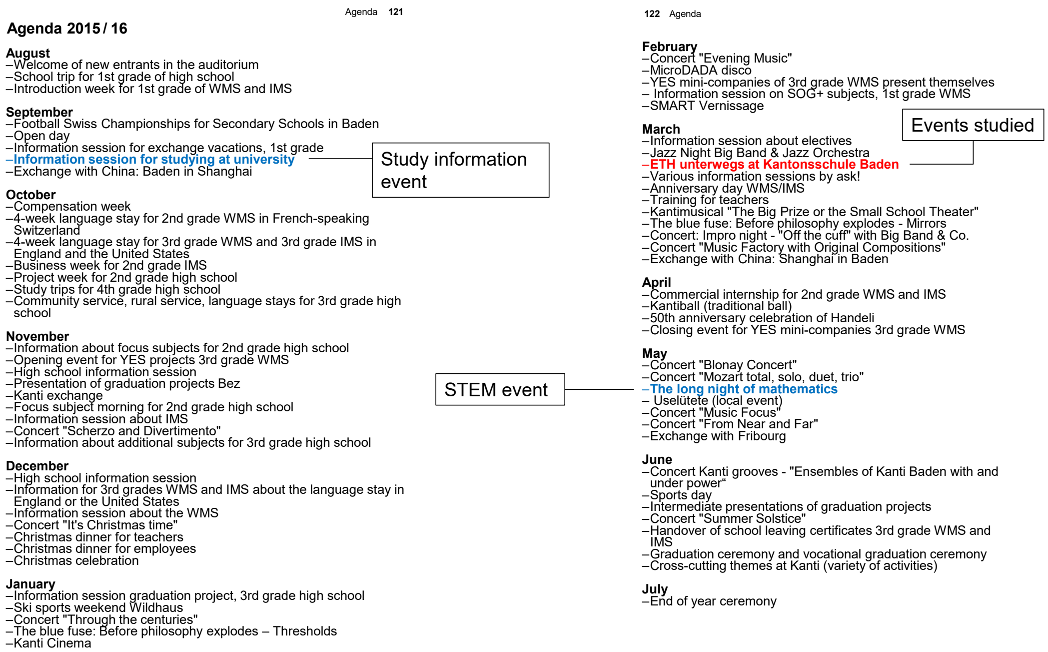


Figure A3: Example: Events and STEM Enrollment at a Selected School

Notes: The figure plots the raw STEM enrollment data for 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

Study information event

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

Events studied

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

STEM event

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.

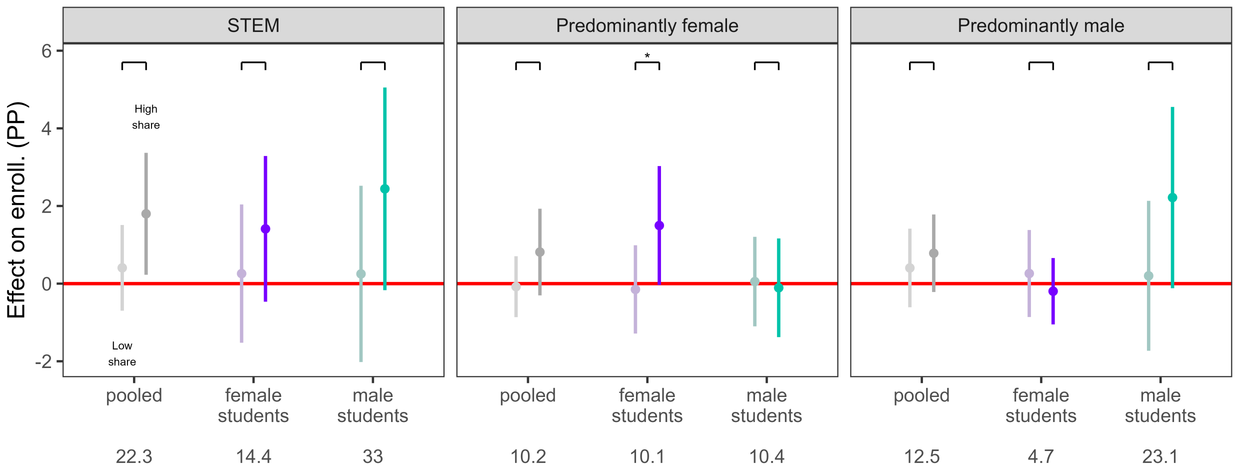
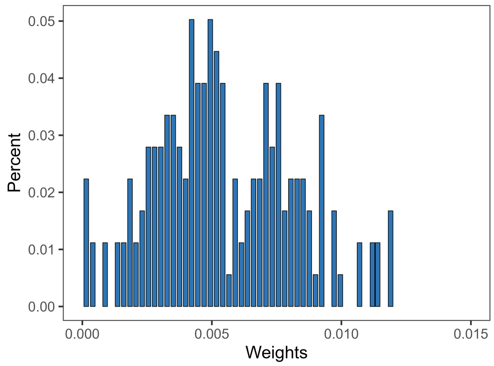
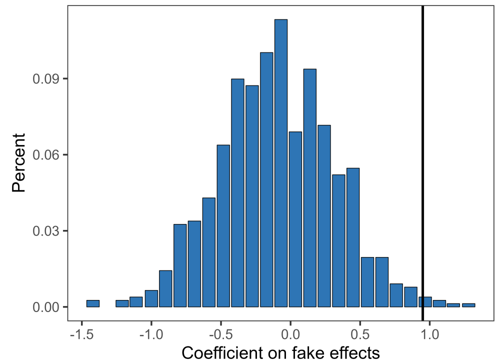


Figure A5: Impact of Event-Level Variation in Speaker Share with Teaching Award on STEM Enrollment

Notes: The figure presents the results for the analysis of changes in speaker composition based on equation (6), 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 at 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 A6: 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.