# Hacking Gender Stereotypes: Girls' Participation in Coding Clubs 

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Employment opportunities and wage growth are rising more rapidly among occupations that require high level of both math and social skills (Deming, 2017; Fayer et al., 2017). The limited participation of women in STEM and coding is still a widespread phenomenon that may result in an insufficient supply of skills required in the labor market (Kahn and Ginther, 2017; Adams and Kirchmaier, 2016). To mitigate this issue, a number of initiatives around the word are trying to promote STEM education among female students or adult women (Del Carpio and Guadalupe, 2021; Breda et al., 2018). Yet, there is limited evidence on the take-up of these intervention and the effectiveness of these projects to increase participation of women and reduce the gender gaps in STEM.

Gender gaps in math start to emerge during childhood and are exacerbated during adolescence, especially in counties with stronger gender stereotypes (Guiso et al., 2008; Nollenberger et al., 2016). Several factors have been shown to influence women's academic self-concept and choice of field of study (Nosek et al., 2002), including parenting (Carlana and Corno, 2021; Chise et al., 2019; Tungodden, 2019), teachers' expectations (Carlana, 2019; Alan et al., 2018), and peers (Brenøe and Zölitz, 2020; Anelli and Peri, 2019). Middle school

[^0]is a key stage of the educational career of students: their identity is still malleable (Riegle-Crumb et al., 2011), but students (and their families) are often taking educational decisions with strong implications for their future, especially in countries characterized by early tracking in high-school (Giustinelli, 2016). While girls who selfselect into scientific training and coding courses may be less prone to stereotypic influences and have higher math achievements (Ertl et al., 2017), it is unclear whether targeting other individuals should be preferred as the returns in the skills acquired may be limited for girls with low pretreatment skills and interests (Di Tommaso et al., 2021). Identifying the characteristics associated with take-up of these types of programs is of crucial importance for designing effective policies to address gender gaps in STEM.

In this paper, we focus on a project aimed at fostering coding and social skills of girls called Girls Code It Better implemented in Italy. We analyze gender gaps in academic interests and perception of barriers to achieve own career goals, as well as how girls applying to the coding clubs differ from those that decide not to apply. First, we show that there are substantial gaps in academic interests since middle school, with girls being less interested in STEM compared to boys despite the higher willingness to attend university. Girls are also more likely to perceive their own gender and their ability as a barrier to achieve their educational goals. Second, we show that girls who self-select into a coding club are different compared to other girls: in our sample, we can rule out a substantial differences in parental education and occupation that may affect take-up, but girls applying to coding clubs have higher interest in pursuing STEM and they are more likely to per-
ceive own gender as a barrier for their educational goals. Programs aimed at increasing girls' interest in STEM may be effective in closing the gender gap if they manage to "hack" gender stereotypes and perceived barriers of high-achieving girls.

The rest of the paper is organized as follows. First, we briefly describe the program and the sample. In the second section we analyze the gender gaps in field interests. Finally, we compare the characteristics of girls who decide to enroll into coding clubs with those who decide not to sign-up. We conclude with a discussion on how coding clubs may help "hacking gender stereotypes".

## I. Data and Experimental Design

## A. Program Description

The program Girls Code It Better (GCIB) has been designed by a private employment agency in Italy and implemented since 2014. It is aimed at mitigating gender gaps in the field of study and workplace by promoting coding skills for girls. The intervention follows the pedagogical principles of Project Based Learning (PBL) (Zecchi, 2012; Condliffe, 2017), with an approach based on "teaching by projects" to foster coding and learning of new technologies (as 3D printing, robotics, web and app design), but also creative thinking, organizational and communication skills. Each coding club includes 20 girls attending the same middle school (between 11 and 14 years old), a teacher from the school and a technology expert (coach maker). Coaches and makers receive a specific training and a manual describing the program protocols, together with centralized support during program development. They act as facilitators of learning rather than instructional teachers, promoting problem solving and encouraging students' motivation. GCIB is offered free of charge to all participating girls and it is implemented in the afternoon at school for around 45 hours per school year. Since 2014, the project has involved around 6,100 girls enrolled in middle schools in most Italian regions.

## B. Sample and Experimental Design

Since 2018, we have collaborated with the implementing partner (Fondazione Officina Futuro) to quantitatively assess the participation and effectiveness of Girls Code It Better. Participation in the program is voluntary but it is limited to 20 girls per school by the resources of the implemented partner and the specific features of the instructional approach. When the number of applicants in a school exceeds 20 , the slots are randomly assigned at individual level, stratified by grade. The compliance rate with the treatment is around $95 \%$ among students invited to participate in the project, suggesting that girls are highly involved in the development of the project.

We collect endline surveys to all students in schools with rationing, including detailed information on family background, aspirations, interests, perception of barriers to achieve career goals. In this paper, we focus on the pilot data collection in 2019, before the COVID-19 pandemic, due to limited sample size in the online surveys collected in 2020 and 2021. The sample includes 16 middle schools and 4,494 students. More information on the data collection and survey questions is available on Carlana and Fort (2022). In the analysis reported in this paper, to ease the interpretation, we transform likert scales into dummies which assumes value 1 if the value reported by the student is higher than the mean of the entire sample.

## II. Gender Gaps

We start by comparing the characteristics of boys and girls in schools that participate in the program. As shown in the first three columns of Table 1, all family background characteristics are balanced (Panel A), but $70 \%$ of girls are interested in applying to university compared to only $54 \%$ of boys. Panel B shows clear gender gaps in academic interests: boys are significantly more likely than girls to like math, have higher interest in STEM oriented high-schools and occupations (such as becoming an engineer, programmer, or scientist). On the other
hand, girls are statistically more likely to like literature and are more interested on classical high-school and non-STEM occupations (such as lawyer or administrative staff). Furthermore, girls are more likely to perceive their own gender and their ability in math as an obstacle to achieve their educational goals. ${ }^{1}$

## III. Girls' Participation Decision

The last three columns of Table 1 shows the mean of each characteristics for girls who applied and did not apply to the program Girls Code It Better, as well as the pvalue of the difference when controlling for school fixed effects. Overall, $16 \%$ of girls in the schools applied to join the coding clubs, as they require an intensive effort after the end of the school day for around 45 hours between November and April. ${ }^{2}$ Girls applying to the coding club are less likely to be immigrants and they have parents with lower education and occupation level, although the difference is not statistically significant at conventional levels. The key difference between the two groups is related to their educational and occupational interests: girls applying to the coding clubs are more likely to report interest in math and to continue their studies into STEM high-school and get a STEM-oriented occupation. However, even among applicants to coding clubs, the share of girls with a high interest in a STEM occupation is still $37 \%$ compared to an average of $55 \%$ among boys, suggesting important margins to affect their career choices. Notably, reach-

[^1]ing self-selected applicants do not substantially reduce the potential for closing gender gap in the interest for STEM occupation as most of these girls still perceive high barriers and are unsure of whether to enroll in further STEM education ${ }^{3}$. At the same time, targeting self-selected candidates offers potential gains: as research on active learning programs suggests (Di Tommaso et al., 2021), it may indeed lead to improved program effectiveness on participants and overall cost-effectiveness. Furthermore, girls who decided to apply to the coding clubs are more likely than other girls to perceive higher barriers in achieving their educational goals due to their own gender. As early as middle school, a substantial share of girls already perceive their own gender as a barrier to a successful career.

## IV. Conclusion

Programs aimed at increasing the participation of girls in STEM education are likely to target girls less affected by gender stereotypical influences in the field of study (Ertl et al., 2017). In this paper, we show that although girls who apply to a coding club have higher interest for STEM compared to other girls who do not apply, there are substantial margins to affect their long-term career and decrease their perception of their own gender as a barrier to achieve their goals. Given the evidence on the effectiveness of intervention aimed at increasing participation of girls in math, they may also be those with the highest potential gain from exposure to STEM (Di Tommaso et al., 2021). There is still a long way to go to close gender gaps, but education programs aimed at increasing STEM participation of girls are a promising avenue to achieve this goal.

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[^2]Table 1—Summary statistics by gender and program enrollment

| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Boys | Girls | P -value | Girls:Applied |  | P-value |
|  |  |  |  | No | Yes |  |
| Panel A: Family Background |  |  |  |  |  |  |
| Immigrant | 0.165 | 0.181 | 0.142 | 0.190 | 0.061 | 0.006 |
|  | ( 0.371) | ( 0.385) |  | ( 0.392) | ( 0.240) |  |
| Mum less than high-school | 0.557 | 0.573 | 0.405 | 0.582 | 0.545 | 0.396 |
|  | ( 0.497) | ( 0.495) |  | ( 0.493) | ( 0.500) |  |
| Mum has a university degree | 0.442 | 0.426 | 0.403 | 0.418 | 0.455 | 0.391 |
|  | ( 0.497) | ( 0.495) |  | ( 0.493) | ( 0.500) |  |
| Mum works in STEM | 0.149 | 0.139 | 0.426 | 0.133 | 0.148 | 0.756 |
|  | ( 0.356) | ( 0.346) |  | ( 0.340) | ( 0.357) |  |
| Mum has a high wage | 0.654 | 0.653 | 0.916 | 0.648 | 0.717 | 0.143 |
|  | ( 0.476) | ( 0.476) |  | ( 0.478) | ( 0.453) |  |
| Dad less than high-school | 0.593 | 0.613 | 0.249 | 0.614 | 0.626 | 0.913 |
|  | ( 0.491) | ( 0.487) |  | ( 0.487) | ( 0.486) |  |
| Dad has a university degree | 0.406 | 0.386 | 0.261 | 0.386 | 0.374 | 0.919 |
|  | ( 0.491) | ( 0.487) |  | ( 0.487) | ( 0.486) |  |
| Dad works in STEM | 0.283 | 0.287 | 0.729 | 0.282 | 0.337 | 0.246 |
|  | ( 0.451) | ( 0.452) |  | ( 0.450) | ( 0.475) |  |
| Dad has a high wage | $0.582$ | $0.582$ | 0.823 | $0.582$ | $0.576$ | 0.945 |
|  | $\text { ( } 0.493)$ | $(0.493)$ |  | $(0.493)$ | $(0.497)$ |  |
| Panel B: Academic Interests |  |  |  |  |  |  |
| Plans: University | 0.543 | 0.700 | 0.000 | 0.691 | 0.707 | 0.454 |
|  | ( 0.498) | ( 0.458) |  | ( 0.462) | ( 0.457) |  |
| Like Math | 0.479 | 0.384 | 0.000 | 0.365 | 0.434 | 0.128 |
|  | ( 0.500) | ( 0.486) |  | ( 0.482) | ( 0.498) |  |
| Like Italian | 0.302 | 0.440 | 0.000 | 0.439 | 0.404 | 0.293 |
|  | ( 0.459) | ( 0.496) |  | ( 0.496) | ( 0.493) |  |
| STEM High-School | 0.415 | 0.372 | 0.004 | 0.354 | 0.444 | 0.042 |
|  | ( 0.493) | ( 0.484) |  | ( 0.478) | ( 0.499) |  |
| Classic High-School | 0.494 | 0.707 | 0.000 | 0.708 | 0.758 | 0.366 |
|  | ( 0.500) | ( 0.455) |  | ( 0.455) | ( 0.431) |  |
| STEM Occupations | 0.547 | 0.334 | 0.000 | 0.308 | 0.374 | 0.079 |
|  | ( 0.498) | ( 0.472) |  | ( 0.462) | ( 0.486) |  |
| Non-STEM Occupations | 0.436 | 0.460 | 0.091 | 0.468 | 0.404 | 0.261 |
|  | ( 0.496) | ( 0.499) |  | ( 0.499) | ( 0.493) |  |
| Panel C: Barriers to achieve Educational Goals |  |  |  |  |  |  |
| Barrier: Gender Unfit | 0.410 | 0.535 | 0.000 | 0.533 | 0.657 | 0.018 |
|  | ( 0.492) | ( 0.499) |  | ( 0.499) | ( 0.477) |  |
| Barrier: Ability Math | 0.349 | $0.437$ | 0.000 | $0.444$ | $0.434$ | 0.687 |
|  | ( 0.477) | ( 0.496) |  | ( 0.497) | ( 0.498) |  |
| Explicit gender stereotypes | 0.557 | 0.344 | 0.000 | 0.351 | 0.354 | 0.725 |
|  | ( 0.497) | ( 0.475) |  | ( 0.477) | ( 0.480) |  |
| Observations | 2244 | 2250 |  | 1885 | 99 |  |

Note: This table presents the summary statistics of the sample: column (1) shows the mean for boys, column (2) the mean for girls and column (3) the difference between the two groups, including school FE. Column 4 and 5 show the mean for girls who did not applied to the program and girls in the control group of the intervention, respectively. The last column shows the p-value of the difference between girls who did not apply and girls who applied, controlling for school FE. The standard deviation are in the parentheses. In column 5 , we consider only girls who apply to the coding course but are not selected to participate as data were collected at endline for all students. Hence, the sum of columns 4 and 5 is lower than column 2. Variables in Panel B and C are dummies which assume value 1 if the value of the variable is higher than the mean in the sample, except for 'Plans: University'.
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#### Abstract

Who are the girls that decide to sign-up for STEM programs and coding clubs? In this paper, we rely on a large set of survey data from students to analyze how female students who apply to the clubs differ from other students in the schools. Girls applying to coding clubs have higher STEM interest, but they perceive their own gender as a stronger barrier to achieve their educational goal. Supporting this pool of female applicants with STEM programs might have a substantial role in affecting their educational and occupational career and closing the gender gaps in STEM.


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[^1]:    ${ }^{1}$ As explained in Section I.B, all variables in Panel $B$ and $C$ of Table 1 are dummies assume 1 if the student report a interest or perception of barrier higher than the mean student in the sample. The only exception is "Plans: University" which assumes value 1 if the student reports that his or her educational goal is to achieve an university degree. As students are invited to report interest for different available types of high-school (e.g. classic vs STEM) and not to submit their personal ranking across alternatives, answers are not mutually exclusive and do not sum to one.
    ${ }^{2}$ Given that we use data collected at endline, to avoid confounding the effect of the treatment with the selfselection, in column 5 we include only girls who applied but were not randomly selected to participate in the program.

[^2]:    ${ }^{3}$ In our case, for example, the interest in STEM occupations for self-selected candidates is 7 percentage points higher than for other candidates ( $0.37 \%$ vs. $0.30 \%$ ).

