Digital skills, university choice and non-cognitive skills: a Randomized Trial*

Pre-analysis Plan

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1 Introduction

Digital skills and STEM degrees undoubtedly continue to gain advantage in defining young workers' opportunities in the labor market. At the same time scholastic curricula, especially in countries dominated by a humanistic view of pre-university education, struggle to include quantitative subjects and the use of modern technologies to a sufficient degree (OECD (2020)). Even where the attention to digital skills and quantitative subjects is greater, we witness a segregation of students' interests by gender, with girls less likely to engage and perform well in this type of education compared to boys (e.g. OECD (2020); Machin and Pekkarinen (2008); Niederle and Vesterlund (2010)). As a result, students who suffered from a lack of exposition to STEM subjects during their schooling – especially girls–, tend to self-select into non-STEM subjects once they join university, and eventually end up in less remunerating occupations (Zafar (2013); Sloane, Hurst, and Black (2019)). Other explanations of lower female enrollment in STEM departments and lower female occupation in STEM jobs relate to non-cognitive skills, such as grit (Alan & Ertac, 2019; Alan, Boneva, & Ertac, 2019).

In this RCT, we randomly expose Italian high school students from different majors[1] to digital skills courses

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[1]Italian schools maintain the same curriculum until eighth grade, and then specialize: high schools (grades 9-13) are classified into technical schools, professional schools and *licei*. Both technical and professional high schools aim at teaching a profession – curricula can be more or less STEM-oriented depending on the specialization, whereas *licei* are aimed at preparing students for university. There are many types of *liceo*, but they are all characterized by the absence of practical classes, with the exception of art-making for the artistic

taught by Fab Labs, and assess the impact of this exposition on students' university choice, their attitude towards quantitative subjects, and the possible mechanisms of action of our treatment: in particular, we focus on grit, creativity, and self-reported confidence with quantitative subjects.

Note: we plan to produce at least two manuscripts from this RCT, investigating different outcome variables. Manuscripts will be authored by different subsets of the authors' list presented above.

2 Empirical strategy

2.1 Context and treatment

Context:

our intervention consists of randomizing access to digital skills' courses offered by Fab Labs. Students will follow courses as part of their school curricula: students are required to complete a number of PCTO credits towards the completion of their high school degree: these are obtained by completing extra courses or by completing internships. The list of activities that students can choose from in order to obtain PCTO credits is defined each year by each individual school. With our intervention, Fab Lab courses will be offered randomly as PCTO activities.

Fab Labs are a network of entities organizing digital skills' courses for firms and students, located in many locations worldwide and coordinated by the Fab foundation, in turn initiated by the Massachusetts Institute of Technology (MIT). The local Fab Labs that will implement our intervention are independent non-profit entities run by employees and specialized in offering children and teenagers courses aimed at reducing the digital gap: all their courses, which follow some pre-set curricula, cover several aspects of digital skills, from programming to the use of modern technologies such as 3D printers and laser cutters (each Lab is equipped with a number of machines). The courses considered in this RCT cover all phases of 3-D printing (from designing to actual printing) and laser cutting, and they adopt a validated and standardized pedagogic approach based on "learning-by-doing".

Treatment:

the Fab Lab courses will be designed in up to 3 ways, i.e. each of the involved Fab Labs will offer 2 or all 3 variations of the treatment based on the total number of students they cover. Variations are included in order to study possibly heterogeneous effects. However, as detailed below, assignment to treatment variations will not be randomized due to institutional constraints. The three variations are:

- Hackaton: students receive training and then compete on the realization of a project based on the acquired skills (the role of competition as a mechanism of gender differences in quantitative subjects' performance has been widely discussed in the literature (e.g. Niederle and Vesterlund (2010)));
- Short course: few class-like sessions over the course of approximately two months, for a total of approximately 10 hours;
- Long course: higher number of class-like sessions over the course of the entire academic year, for a total of approximately 20 hours.

liceo, and by a reduced attention to mathematics and other quantitative subjects compared to other European countries, even for the scientific *liceo* where they are supposed to be of primary importance.

2.2 Design

This is a **clustered, stratified randomized experiment** with a **single treatment**, where clusters are classes and strata are schools, such that:

- **C**: classes assigned to placebo treatment (denoted as "C") can have access to PCTO courses other than Fab Lab courses;
- **T**: classes assigned to active treatment (denoted as "T") have access to Fab Lab courses for their PCTO credits, though each student can freely choose: (i) whether to sign up to Fab Lab courses; (ii) to which course they wish to sign up.

Although ideally one would like to randomize access to different variations of the treatment, each course format covers the same digital skills in a different number of hours, and students might have different amounts of PCTO credits (hours) left to cover. In absence of an extremely large (unattainable) sample size, randomizing treatment variations is unfeasible: in the current sample, we foresee that assigning entire classes to accessing only one variation we would obtain too limited participation to attain the desired power. We will however collect baseline data on the number of PCTO credits (hours) needed by each student, as well as other possible determinants of their course format's choice.

Since baseline variables are collected for all students, we will assess and describe self-selection of participants in different treatment variations by running choice models (e.g. MLN) within each school and in the overall sample.

Our **population of interest** consists of Italian high school students. Our sample consists of approximately 1500 students in 10 schools, located in 5 cities across the country, for a total of approximately 60 classes.
Each city is served by a different Fab Lab: **randomization is stratified** at the school level, since each Fab Lab works with one school (with the exception of a single Fab Lab working with 6 schools). This is to ensure that each participating schools has access to Fab Lab courses for a pre-specified percentage of classes in the study. Randomization is carried out in R: we assign to treatment 70% of classes. The classes taking part to the study are chosen in accordance with school principals based on two criteria:

1. The expected number of treated classes must be sustainable in terms of the local Fab Lab resources (number of employees, activities carried out by the Fab Lab);
2. **Exclusion criteria**: classes that, at baseline, were already assigned to a pre-determined PCTO activity (e.g. by choice of a teacher) cannot participate in the study;

2.3 Outcomes

We will collect data on three outcomes, which will constitute the outcome of interest of separate manuscripts and act as covariates in the others:

1. Self-reported students' preferences for STEM subjects;
2. Grit;
3. Creativity.

We will measure preferences over subjects both at baseline and endline in the form of:

- Preference over school subjects;
- Interest over potential future university course of study;
- Interest over potential future occupations.

We will measure grit and creativity at baseline using scale-based measures, namely:

- For grit: Duckworth scale (Duckworth, Peterson, D., and Kelly (2007));
- For creativity: a survey question from the "PISA creative thinking framework" (OECD, 2021), a question from the Alternative Uses Test (Guilford, 1967), and the 10 question from the psychometric short scale of creative self ((Karwowski, Lebuda, & Wiśniewska, 2011))

At endline, we will repeat the same scale-based measurement and add an incentive-based task-based measure, which we do not include at baseline as we believe it might be a transformative treatment, namely it could increase subject's interest in STEM subjects per se, and affect both compliance among the treated and outcome measures in both treatment groups.

After the completion of the task, students will be asked to report what online sources they have used, if any, and to self-report their impressions on the task (whether they got anxious, how difficult they found it).

The task is administered along the endline survey, which is conducted under direct supervision, during regular school time.

2.4 Phases of the study

The phases of the study are the following:

- April 2021 - October 2021: researchers provide employees of participating Fab Labs with the necessary training. Training concerns understanding the importance of randomization, administration of baseline surveys and presentation of courses to treated classes, consistency of treatments across Fab Labs, presence of an endline survey;
- Summer 2021: Ethics Review Board application - (Approval obtained in July 2021);
- September - October 2021: Fab Labs send the list of classes to researchers, divided by school, researchers proceed with stratified randomization;
- November 2021: Fab Lab employees and researchers will (i) present Fab Lab courses in classes assigned to active treatment and (ii) conduct a baseline survey in all classes (both **C** and **T**) during regular school time and under direct supervision;
- December 2021 - April 2022: Fab Lab conduct courses directly in participating schools;
- May 2022: Fab Lab employees and researchers administer the endline survey to all classes, during regular school time and under direct supervision;
- Starting in summer 2022: data analysis and manuscripts redaction.

2.5 Benchmark model

In the entire sample, for each measurement of each outcome variable Y, we aim at estimating Local Average Treatment Effects (LATE) with clustered ANCOVA regressions. Let i index individual students:

$$Y_i = \beta_0 + \beta_1 \text{Fab Lab course}_i + \boldsymbol{\gamma}^{\intercal} \boldsymbol{X_i} + \text{Y-baseline}_i + \varepsilon_i$$

Where (Fab Lab course) is a binary variable indicating actual take-up of treatment, and β_1 will be estimated by IV with binary treatment assignment as an instrument. Standard errors are clustered at the class level and $\boldsymbol{X}$ is a vector of baseline covariates collected in the baseline survey. We will present p-values corrected for multiple hypotheses.

2.6 Heterogeneity analysis

We will assess heterogeneity of the treatment effect by:

- Gender;
- Treatment variation;
- Relevant baseline characteristics, in particular significant determinants of compliance with treatment among the treated, and significant determinants of compliers' choice of treatment variation (Fab Lab course format).

2.7 Robustness checks

We plan to conduct robustness checks to be defined in light of compliance.
Among these, in order to draw causal inference on the effect of treatment variations, we plan to use matching estimators where feasible (i.e. in presence of sufficient overlap in baseline covariates).

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A Baseline survey, list of variables

Attitude towards STEM subjects	Attitude towards mathematics (PISA framework)
	Preferred and least preferred subjects at school
	Occupational aspiration
	Expectation on college enrollment
	Self-reported GPA
	Expectation on field of study conditional on college enrollment
	Attitude towards possibility to study a STEM subject at university
Non-cognitive skills	Grit (Duckworth short scale)
	Creativity (several scales)
Demographics	Gender
	Exact age
	Number of siblings
	Order of birth (first born dummy)
Parents' characteristics	Mother's education (college dummy and field conditional on college)
	Father's education (college dummy and field conditional on college)
	Parents education (dummy)
	Presence of a family commercial activity (dummy)
Information from schools	Number of students per class
	Class major
	Female share of students per class
	Class grade