Preparing students for the digital era: lessons learned from FabLabs in school

M. F. Ferracane, V. Ballerini, A. De Falco, A. Dominici, F. Menchetti, S. Noirjean

Martina Francesca Ferracane, European University Institute
Florence, Italy, martina.ferracane@eui.com

Veronica Ballerini, University of Florence
Florence, Italy, veronica.ballerini@unifi.it

Adriano De Falco, European University Institute
Florence, Italy, adriano.defalco@eui.eu

Alice Dominici, European University Institute
Florence, Italy, alice.dominici@eui.eu

Fiammetta Menchetti, University of Florence
Florence, Italy, fiammetta.menchetti@unifi.it

Silvia Noirjean, University of Florence
Florence, Italy, silvia.noirjean@unifi.it

Abstract

In this study, we randomly expose Italian high school students from different majors to creative activities taught by FabLabs and assess the impact of this exposition on students' career aspirations, university choice, interest and confidence in STEM university courses, attitude towards STEM subjects, creativity, and grit. We find that giving students the possibility to join FabLab activities has overall a positive impact on all the variables assessed, except for career aspirations and creativity. This working paper represents a preliminary assessment and is limited to estimating the effect of having the possibility to join FabLab activities. A refined analysis will also investigate the effect on students who have participated in the activities, for whom we expect to find a stronger positive effect.

Keywords

Causal inference, Creativity, FabLab, Grit, STEM, digital skills

1 Introduction

In the last three decades, technological revolution and the so-called 'servicification" of the economy have represented the main drivers of economic growth, leading to major changes in the labor market and, in turn, in the technical, cognitive, and non-cognitive skills required. However, the educational systems are struggling to adapt to this new reality. According to the OECD Survey of Adult Skills (PIAAC), over 40% of workers lack the skills to use digital technology in the workplace. One of the drivers may be related to school curricula struggling to include quantitative subjects and the use of modern technologies to a sufficient degree (OECD, 2020).

The workers of the future need to be able to solve unstructured problems, work with new information, and carry out non-routine tasks (Levy & Murnane, 2013). It is expected that a wide range of occupations will require a higher degree of cognitive abilities such as creativity, logical reasoning, and problem sensitivity as part of their core skills (WEF, 2015) and the value of skills needed for non-automatable tasks, such as social skills, will also increase (Autor, 2015; Deming, 2015). Although creativity in schools is typically equated to the teaching of arts, its definition includes the ability to problem-solving and producing original

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and useful ideas, which are abilities as central in STEM (e.g., in engineering practice, Sheppard et al., 2008) as they are in non-STEM jobs.

Beyond cognitive skills, workers need to develop no less critical non-cognitive skills, such as grit and teamwork, to adapt to the ever-changing labor market (e.g., Collard and Looney, 2014). Duckworth *et al.* (2007) define grit as passion and perseverance for long-term goals. Grit turned out to be highly predictive of success in various educational and occupational settings (e.g., Duckworth *et al*., 2011; Maddi *et al*., 2012), which can be partly explained by the fact that the willingness to challenge oneself is strongly linked to actual achievement. Such non-cognitive skills have often been considered unchangeable traits. Nonetheless, many studies suggest that it is possible to design educational interventions aimed at fostering them; see Almlund *et al*. (2011), Kautz *et al.* (2014), and Alan & Ertac (2019), among others.

In this study, we conduct a Randomized Controlled Trial (RCT) that randomly exposes Italian high school students from different majors to creative courses taught by FabLabs to assess the impact of this exposition on students' career aspiration, university choice, their attitude toward STEM subjects, enhancement of creativity and grit. We also investigate, for what concerns STEM subjects, the possible mechanisms of action of our treatment: in particular, we focus on self-reported confidence with quantitative subjects.

2 Setting

Our intervention consists of giving access to creative activities offered by FabLabs to randomly selected high school classes.

2.1 FabLab

A FabLab (fabrication laboratory) is a small-scale workshop offering (personal) digital fabrication. The first time when digital fabrication equipment, including 3D printers, CNC machines, and electronics, was packaged in a standardized low-cost lab was at the Massachusetts Institute of Technology (MIT) in 2002 (Blikstein and Krannich, 2013). This is where the concept of Fabrication Laboratory or 'FabLab' was born. The founder of the FabLab concept, Prof. Neil Gershenfeld, describes this digitalization of fabrication as the process "where you do not just digitize design, but the materials and the process" (Solon, 2013), so digital fabrication is about "bringing programmability to the real world".

Since then, the concept of FabLabs spread all over the world, not only in universities (more rarely in schools) but also as private or public spaces designed for entrepreneurs or more widely for anyone interested in creating something. The spread of digital fabrication labs has been triggered by a drop in the cost of digital fabrication tools. In fact, in the early 2000s, prototyping equipment, such as laser cutters and 3D printers, dramatically dropped in price. In 2009, the expiration of patents on FDM 3D printing led to a further drop in the price of desktop 3D printers (Bensoussan, 2016). Moreover, open-source software further popularized these technologies.

This radically transformed the nature of product engineering as it became much cheaper and quicker to test new ideas and introduce tweaks in the prototype until the optimal result was reached. Beyond applications in prototyping, digital fabrication labs - or "makerspaces-"[21] have become a reference point for Do-It-Yourself (DIY) enthusiasts that were looking for the right tools and environment to experiment with their creativity. In these labs, anyone can make use of digital fabrication tools to create anything they consider useful, valuable, or simply fun. Projects done in FabLabs range from jewelry to furniture and all the way up to entire houses. In FabLabs, the maker can also create something that does not exist today, but that they feel would be cool to make.

[21] The Maker movement can be defined as a grassroots culture dedicated to hands-on making and technological innovation (Peppler *et al*., 2016).

Tinkering is an important component of the making process. It is about solving problems related to the development and realization of innovative ideas in a creative, iterative, and open-ended manner (Petrich *et al.*, 2016). An important part of the makers' culture is that ideas and projects are freely shared among makers, and this makes it possible to access a vast amount of know-how online, including the projects mentioned earlier on DIY virtual reality glasses or on how to build a DIY lab for scientific experiments.

2.2 FabLabs in school

Most of the projects FabLabs has been used for, however, have remained in the realm of prototyping and higher education. It was only in 2008 that the space saw the first conceptualization of a project with an explicit focus on primary and secondary education—with Stanford University's FabLab@School project. Since then, especially in a selected number of countries, there has been a growing interest among educators in primary and secondary schools regarding how to incorporate "making" into the classroom. Despite the novelty of this approach, making has been shown to support the development of an array of learning dispositions, including resourcefulness, creativity, teamwork, and forms of adaptive expertise (Bevan, 2017, citing Martin & Dixon, 2016; Peppler, 2016; Ryan *et al*., 2016). In fact, the idea of 'playful experimentation' with tools and material is a powerful one in the context of learning (Regalla, 2016). When children make things with their hands, they are engaged in active learning while having fun (*Ibid.*).

The recent studies on bringing a culture of making into schools through workshops and the adaptation of the academic curriculum suggest that students develop proficiencies, as well as interest, in design and engineering practices (Berland 2016; Kafai *et al*. 2014). Moreover, students develop identities as creative thinkers and problem solvers (Martin and Dixon 2016). Making is also frequently interdisciplinary in nature. Interdisciplinary learning is another important element in the education of 21st-century citizens and workers, who will be faced with increasingly complex and interdisciplinary challenges. This approach can leverage a reform of today's highly siloed education that reflects an older vision of the world, where workers were often doing the same routine tasks for their entire careers. However, the reality is now different, and technological trends are creating new cross-functional roles, for which employees will need to adapt to new roles with the help of technical, social, and analytical skills (WEF 2016).

Through the process of digital design and fabrication, students experience "novel levels of team collaboration" (Blikstein 2013), and learners frequently directly request help from or offer it to one another, inspire or are inspired by others' new ideas or strategies for troubleshooting, and physically build on or connect their own work to the existing body of work of a fellow tinkerer (Bevan 2017, citing Gutwill et al. 2015). More generally, a recent review of the literature on making in education by Bevan (2017) shows that there is a growing body of evidence on the many ways in which making can motivate and support learners' activity, position STEM practices (that is science, technology, engineering, and mathematics) as a powerful tool to engage in interest-driven activity and leverage cultural resources with the goal of deepening engagement and learning. Making in education can therefore be a tool to prepare our students with critical foundational competencies, competencies, and character qualities needed in the 21st century. By learning how to learn and make use of the process of tinkering, students also learn the power of learning from mistakes, and they refine their skills through experience and persistence. By cultivating a nimble perspective toward problem-solving, developing curiosity, and becoming comfortable with "not knowing," students develop a maker's mindset that will be extremely valuable in an ever-changing job market (Regalla, 2016).

However, the application of making in schools is still very recent, and today most of the makers' activities are primarily located in private and affluent schools, museums, and higher education (Bevan 2017; Blikstein & Worsley 2016). Most of the evidence available on the impact of FabLabs in schools is anecdotal and, to our knowledge, there are no randomized controlled trials performed to assess the impact of FabLab activities proposed to students in high schools.

2.3 Context of the courses

Students who participated in the program are enrolled in different Italian high schools, from the second to the fifth (and last) grade. With our intervention, FabLab activities were offered to students in randomly selected classes. The activities offered by the FabLabs across the different universities were harmonized across the FabLabs involved in the study, and activities were carried out directly inside schools by FabLab employees (they all received the same set of instructions from the investigators). The number of high schools that participated in the intervention is 5, with a total number of classes equal to 42.

Five FabLabs located in different parts of Italy participated in the intervention. As depicted in Figure 1, they are in the cities of Verona (Veneto), Schio (Veneto), Ancona (Marche), Mantua (Lombardy), and Agrigento (Sicily). The local FabLabs that implemented our intervention are independent non-profit entities run by employees and specialized in offering activities with the aim of reducing the digital gap: their courses cover many aspects of digital skills, from programming to the use of modern technologies such as 3D printers and laser cutters (each Lab is equipped with several machines).

Figure 1: The five FabLabs in the RCT.

Among the schools contacted by FabLabs and that decided to be part of the experiment, the vast majority are of two types: *Istituto Tecnico* (Technical School) and *Liceo Artistico* (Artistic school)[22]. For both types of schools, these courses are more likely to complement their curricula. In fact, whereas their curricula are more focused on practical subjects than other schools, the specific skillset covered by FabLab courses (e.g., 3D printing, laser cutting, programming) is not part of their curricula. On the other hand, these schools have the lowest enrollment in university (especially in STEM subjects) among Italian high schools and are also likely to attract the least gritty among students. The reason is that during the last year of middle

[22] Within one of these schools, there are three classes of *Liceo Scientifico*, a school with a curriculum specialized in sciences: two of these are assigned to treatment.

school, right before choosing the high school curricula, Italian students are offered an official curriculum suggestion by their teachers; *Liceo Artistico* and technical schools are typically indicated to students who have lower grades in STEM subjects and appear to be less resistant and gritty. Therefore, we are focusing on schools where FabLab courses have a large potential to affect students' characteristics and choices.

2.4 Treatment

FabLab activities courses could be designed in up to three ways, meaning that each of the involved FabLabs will offer two or all three variations of the treatment based on the total number of students they cover. The options are the following:

- *Hackathon*: students receive training and then compete on the realization of a project based on the acquired skills.
- *Short course*: few class-like sessions from 2 hours to 20 hours.
- *Long course*: higher number of class-like sessions, from 20 hours to 150 hours across the entire academic year.

The activities have been designed and managed by Fondazione Edulife, as part of the Fab school project funded by Fondazione Cariverona.[23]

For the rest of the paper, we treat the three modalities as a single treatment. In other words, we will assess the effect of receiving the possibility to enroll in a FabLab course regardless of its specific characteristics. At this preliminary stage, we are still collecting information on which students attended the different activities. We leave this to future analyses, where we intend to investigate the effect of different types of courses on both the extensive (who did what) and the intensive margin (how many hours were attended).

3 Outcomes and Hypotheses

In this Section, we describe our primary and secondary outcomes and our hypotheses concerning the effects of FabLab courses.

3.1 Primary outcomes

Career Aspiration We conjecture that exposure to FabLab activities may guide students toward a STEM career, or more generally to higher skilled jobs as most of the involved classes belong to technical high schools, which typically train to be technical workers, e.g., electricians and mechanics. We assess the career aspiration by asking students which job they would like to do once they finish studying. We define the outcome variable $Y_{STEM,i}$ as a binary indicator that takes value 1 if the student i declares they want to pursue a STEM career; similarly, referring to technical workers, we define a second binary variable, $Y_{TECH,i}$.

University Choice We test whether the Fablab activities alter human capital decisions. We expect students may decide to enroll in university to follow STEM courses; it could happen both at the intensive and extensive margin, meaning this could affect both students who were undecided regarding enrolling in university and students who wanted to enroll in different majors. We measure it by asking students whether they intend to enroll in university and, in any case, if they would choose a STEM major. Accordingly, we define the outcome variables related to the university choice as two binary indicators: $Y_{U1,i}$ takes value 1 if the student i declares they will go to university; $Y_{U2,i}$ is 1 if they say they will enroll in a STEM major and 0 otherwise.

Grit FabLabs leverage a learn-by-doing approach that is expected to foster grit. We adopt the *Short Grit Scale* (Grit–S) for measuring this construct (Duckworth & Quinn, 2009). The Grit-S is short, i.e., consisting

[23] More information about the project can be found at the project's website: https://fabschool.it/

of only eight items, and has proven to have good psychometric properties. Our outcome variable is the mean score over the eight items, i.e., $Y_{G,i}, \forall i = 1, \dots, N$.

Creativity FabLabs stress the role of creativity in their activities and its importance for some STEM-related careers. We, therefore, test whether FabLab activities increase creativity. We measure this construct by asking both survey questions from the "PISA creative thinking framework" (OECD, 2021) and a question from the Alternative Uses Test (Guilford, 1967). Also, we administered the Short Scale of Creative Self (SSCS; Karwowski, Lebuda & Wisniewska, 2011), i.e., a self-reported five-point Likert scale consisting of eleven items: six of them measure creative self-efficacy (CSE) and five measure creative personal identity (CPI). These two self-concept constructs are gaining popularity in the creativity literature (Karwowski, 2012): CSE measures the ability to solve problems requiring creative thinking, and CPI reflects the belief that creativity is an important element of individuals' functioning. We assess the treatment effect on the overall self-reported creativity and the CSE and CPI constructs. For all i's, we indicate the former with $Y_{SSCS,i}$ measured as the average score over the 11 items of the SSCS; similarly, $Y_{CSE,i}$ and $Y_{CPI,i}$ is the averages over the items related to the two sub-scales.

3.2 Secondary outcomes

We collected secondary outcomes in the Endline survey to explore possible mechanisms.

Attitude toward STEM subjects in schools We estimate whether preferences over school subjects change due to the intervention. We conjecture that students may be more willing to engage with STEM subjects in school, that include math, physics, chemistry, science, computer science, mechanics, electronics, robotics and technical lab activities. Therefore, we assess the treatment effect on (i) an indicator variable $Y_{FavSubjSTEM,i}$ that takes value 1 if student i ranks a STEM subject among the first two favorite subjects, and (ii) a categorical variable $Y_{STEMSubj,i}$ ranging from 1 to 5, depending on how much the student i likes STEM subjects. Moreover, we test whether the self-reported grade point average (GPA) is altered by the treatment ($Y_{GPA,i}$). [24]

Interest and Confidence in STEM careers at university We collect interest and self-reported ability, or confidence, in approaching STEM careers at university. We ask whether student *i* is interested in enrolling in a STEM major at university ($Y_{intSTEM,i}$ = 1 if yes) and whether they feel confident in pursuing a STEM major ($Y_{confSTEM,i}$).

Summarizing, we denote with {*Y*} the set of outcomes of interest and define it as

$$\{Y\} = \{Y_{STEM}, Y_{TECH}, Y_{U1}, Y_{U2}, Y_{G}, Y_{SSCS}, Y_{CSE}, Y_{CPI}, Y_{FavSubjSTEM}, Y_{STEMSubj}, Y_{GPA}, Y_{intSTEM,i}, Y_{confSTEM,i}\} \quad (1)$$

In Section 6, we assess the effect of the assignment to treatment on each of the outcomes.

4 Setting and Data

We perform a clustered, stratified randomized experiment with a single treatment, where clusters are the classes and strata are the schools, such that:

- Control group (C): Classes do not have access to FabLab courses, and
- Treatment group (T): Classes have access to FabLab courses, although each student can freely choose whether to sign up.

[24] For future analyses, we are collecting information also on grades provided by schools for each subject.

Each city is served by a different FabLab: randomization is stratified at the school level; this is to ensure that each participating school has access to FabLab courses for a pre-specified percentage of classes in the study. The probability of being assigned to the treatment is $p = 0.7$.[25]

4.1 Population of interest

Our sample consists of Italian students in 5 schools located in 5 cities across the country (see Figure 1), for a total of 42 classes. We collected information both before (at the *Baseline* survey) and after the intervention (at the *Endline* survey). The number of students who replied at the Endline is 710; yet, we have both Baseline and Endline information for 578 students. Throughout the paper, we refer to these two samples as "full sample" and "matched sample," respectively. In principle, the missing data in the matched sample might be not-at-random (MNAR; Rubin, 1976), implying that the two samples may refer to two different populations; for this reason, we mainly focus on the full dataset. It is worth mentioning, however, that using baseline information would allow using additional covariates, thereby greatly increasing the goodness of fit of the models. Therefore, we also show some results obtained by referring to the matched sample, i.e., restricting the full sample to those present at the Endline but also at the Baseline survey.

	Full sample (N = 710) (Endline information)		**Matched sample** (N = 578) (Baseline information)	
	Mean	SD	Mean	SD
STUDENTS DEMOGRAPHICS				
Not a Male (1/0)	0.346	0.476	0.382	0.486
Age	16.542	1.309	16.112	1.313
Firstborn (1/0)	0.499	0.500	0.509	0.500
Family business (1/0)	0.345	0.476	0.351	0.478
No. of working parents (0-2)	1.763	0.445	1.744	0.449
Any parent has a university education (1/0)	0.330	0.470	0.320	0.467
BASELINE OUTCOMES				
Willingness to attend university (1/0)			0.433	0.496
Self-reported Ability STEM major (1/0)			0.34	0.47
Self-reported Interest STEM major (1/0)			0.40	0.49
Self-reported GPA (1-10)			7.2	0.98
Grit (1-5)			3.254	0.667
Creative self-concept (1-5)			3.777	0.649
Creative self-efficacy (1-5)			3.767	0.668
Creative personal identity (1-5)			3.789	0.714

Table 1: Summary statistics. Note: The information reported for the full sample is that collected during the Endline survey; the information reported for the matched sample is that collected during the Baseline survey.

Table 1 reports some descriptive statistics for our samples of students, both the full and the matched ones. As it is evident from the Table, background characteristics are almost invariant in the two samples, which would support a Missing-At-Random (MAR) assumption, i.e., the assumption that those who were not present at the Baseline survey are not systematically different from those who were present at that occasion and did respond. Both samples are mostly composed of males with a mean age of 16/16 years and a half. Most of them have parents with no university education, both working but not running a family business. Concerning the values of the baseline outcomes, we observe that more than 43% of the students

[25] The main reason why we chose to have more treated in the sample is that we anticipated imperfect compliance; not all treated students enrolled in the courses.

were willing to attend university; a smaller proportion report feeling confident (34%) or even interested (40%) in pursuing STEM majors. On average, students show a high GPA (more than 7/10), and quite high self-reported levels of non-cognitive abilities; in particular, the 95% confidence interval for creativity is above 2.5/5.

5 Balance of the covariates

We randomized before administering the baseline survey to students. In Table 2 we present the results of balance checks.[26] The results are produced by estimating the following model for every covariate X_k with $k = 1, \dots, K$.

$$X_{k,i} = \alpha_{0,k} + \alpha_{1,k} Treat_i + \alpha_{2,k} School_i + \eta_{k,i}\ , \quad i = 1, \dots, N\ ,$$

where $Treat_i$ takes value 1 if student i belongs to a treated class, and 0 otherwise. While the unit of observation is the student, standard errors are clustered at the class level (the level of assignment to treatment; Abadie et al., 2017). As we can notice from Table 2, there are no significant differences in covariates between treated and controls.

	N	Control	Obs. C mean	Treated	Obs. T mean	$\hat{\alpha}_{1,k}$	p-value
STUDENTS DEMOGRAPHICS							
Not a Male (1/0)	710	210	0.65	500	0.62	-0.03	0.64
Age	710	210	16.72	500	16.44	-0.12	0.42
First Born (1/0)	710	210	0.48	500	0.50	0.02	0.64
Family Business (1/0)	710	210	0.36	500	0.32	-0.01	0.66
No. of working parents (0-2)	710	210	1.76	500	1.76	0.00	0.91
Any parent with university education (1/0)	710	210	0.3	500	0.34	0.04	0.32
	N	Control	Obs. C mean	Treated	Obs. T mean	$\hat{\alpha}_{1,k}$	p-value
BASELINE OUTCOMES							
Willingness to attend university (1/0)	568	116	0.38	412	0.45	0.07	0.22
Self-reported STEM Ability major (1/0)	568	116	0.44	412	0.39	-0.05	0.39
Self-reported STEM Interest major (1/0)	568	116	0.45	412	0.42	-0.03	0.43
Self-reported GPA (1-10)	568	116	7.12	412	7.22	0.1	0.21
Grit (1-5)	568	116	3.26	500	3.25	-0.02	0.79
Creative self-concept (1-5)	568	116	3.73	500	3.79	0.05	0.43
Creative self-efficacy (1-5)	568	116	3.73	500	3.78	0.03	0.59
Creative personal identity (1-5)	568	116	3.74	500	3.81	0.06	0.33
	N	Control	Obs. C mean	Treated	Obs. T mean	$\hat{\alpha}_{1,k}$	p-value
CLASS CHARACTERISTICS							
Class size	42	15	16.5	27	19	2.25	0.11

Table 2: Balance Table.

[26] Note that the number of students in the study is higher than the one presented for the pre-analysis plan. We are in the process of matching information of the list of students provided by schools and baseline information collected from the researchers

6 Model and Results

In the entire sample, for each outcome variable $Y_h \in \{Y\}$ defined in (1), we aim to estimate the Intention to Treat (ITT) with clustered ANCOVA regressions. In this setting, we define the ITT as the possibility to access FabLab courses, and thus, we estimate the effect of the treatment *assignment*.

For each h, we assume the following model:

$$Y_{h,i} = \beta_{0,h} + \beta_{1,h} Treat_i + \gamma_h X_i + \varepsilon_{h,i}, \qquad \forall i \tag{2}$$

Our parameter of interest is β_1, estimating the average ITT. Standard errors are clustered at the class level. X is a vector of baseline covariates, which includes school fixed effects, an indicator for being a male, any of the two parents with a university degree, being firstborn, number of working parents, and age. In addition, when estimating the models for the matched sample, we also include baseline covariates reported in Table 2. In the next subsections[27], we present the results on the outcomes introduced in Section 3.

6.1 Results on Primary Outcomes

Career Aspiration

Around 50% of individuals in the sample sustain that they still do not know what their career will be. We do not find that the possibility of joining the activities leads more students to clear their minds about their future. In particular, students from treated classes are less likely to indicate they will be *technical workers*. We conjecture that students may be more attracted to *STEM professionals* careers, which increase by 3 percentage points (60% of the observed controls' mean); however, we lack statistical power to detect a precise effect. We do not note any effect on entrepreneurial ambitions.[28] Note, however, that the results need to be taken with a grain of salt due to the possible re-codification of jobs that may happen in the future. Results do not change if we restrict the analysis to the matched sample, as shown in columns 3 and 4 of Table 3. They show similar qualitative patterns, and the estimates are fairly close to the ones presented for the full sample.

	Full Sample		**Matched Sample**	
	Y_{TECH}	Y_{STEM}	Y_{TECH}	Y_{STEM}
$\hat{\beta}_1$	-0.06*	0.03	-0.05*	0.04
	(0.033)	(0.024)	(0.03)	(0.023)
Observed controls' mean	0.10	0.05	0.08	0.05
School Fixed Effect	√	√	√	√
Controls	√	√	√	√
Adj. R^2	0.2	0.14	0.07	0.07
N	710	710	578	578
*p<0.1, **p<0.05, ***p<0.01.				

Table 3: Results regarding career choices. Note: The table presents estimates for $\beta_{1,h}, h = A$ in equation (2). Standard errors, in parenthesis, are clustered at the class level.

University Choice

The possibility of joining the activities offered by FabLabs shaped short-term decisions about university choices. Looking at Table 4, we can see that students in treated classes are 8 percentage points (p.p.) more

[27] We will present p-values corrected for multiple hypotheses in the next future.

[28] Results on other categories are not shown here. They are imprecisely estimated close to zero.

likely to declare they will go to university. Despite not observing the actual enrolling behavior, we believe this is likely to be impacted, considering that only 39% of students at the baseline show the intention to enroll in university, leading to a 20% probability increase. Interestingly, the increase in university enrollments seems to be driven by STEM majors.[29] Students in classes where FabLab activities were available are 6 p.p. more likely to declare they will enroll in a STEM major, which maps into a 25% increase. Again, the magnitude seems to suggest that actual enrollment behavior will likely be affected. Using the matched sample, we cannot draw the same conclusions. As we can see from Table 2, the treatment slightly correlates with the intention to go to university at the baseline; when we control for it, the estimates in column 3 are less clear. The estimated effect halves and become marginally insignificant (p-value close to 11%). However, the results regarding enrollment in STEM majors remain robust, despite the use of the matched sample and the inclusion of baseline covariates.

	Full Sample		**Matched Sample**	
	Y_{U1}	Y_{U2}	Y_{U1}	Y_{U2}
$\hat{\beta}_1$	0.08**	0.06*	0.04	0.06*
	(0.03)	(0.034)	(0.026)	(0.034)
Observed controls' mean	0.39	0.24	0.40	0.25
School Fixed Effect	√	√	√	√
Controls	√	√	√	√
Adj. R^2	0.2	0.14	0.40	0.34
N	710	710	578	578
*p<0.1, **p<0.05, ***p<0.01.				

Table 4: Results regarding university choices. Note: The table presents estimates for $\beta_{1,h}, h = U1, U2$ in equation (2). Standard errors, in parenthesis, are clustered at the class level.

Grit

Non-cognitive skills are typically more difficult to predict since they can be influenced by various unobserved factors such as parents' influence or individual personality traits; thus, including pre-treatment grit levels in our models may be an effective way to reflect such unobserved information. When controlling for the baseline grit level, we find that the possibility of joining FabLab activities had a significant positive impact on students' grit; the treatment assignment leads to an increase of 0.102 points, roughly corresponding to a 3.2% increase over the controls' grit level. In addition, we find that the willingness to attend university is positively associated with grit (Table 5). Conversely, when we do not consider the baseline grit, the model fit is poor, and the treatment effect is not significant. The estimated causal effect for both the full sample and the matched subsample are shown in Table 5.

Creativity

As of October 2022, we could only test the impact of FabLab activities on self-reported creativity since the creativity assessment under the "PISA creative thinking framework," and the Alternative Use Tests are still ongoing. The estimated causal effect of these preliminary analyses on the full and matched samples is shown in Table 5. The variable "Self-Concept" indicates the overall score, whereas the variables "Self-Efficacy" and "Personal Identity" indicate the scores obtained, respectively, on the CSE and CPI subscales. We find no evidence of causal effects on self-reported creativity at this analysis stage, neither in the full sample nor in the matched subsample. However, across both groups, self-reported creativity is lower among females, and first-born children perceive themselves to be more able to solve problems requiring

[29] The results are qualitatively robust to different sets of STEM major definitions. It is robust to the exclusion of post-high school specialized technical courses, which are not generally considered a degree.

creative thinking.[30] We look forward to comparing individual perceptions with objective creativity measurements.

	Full Sample				Matched Sample			
	Y_G	Y_{SSCS}	Y_{CSE}	Y_{CPI}	Y_G	Y_{SSCS}	Y_{CSE}	Y_{CPI}
$\hat{\beta}_1$	0.065	0.030	0.013	0.050	0.102***	0.040	0.032	0.054
	(0.049)	(0.054)	(0.057)	(0.058)	(0.032)	(0.063)	(0.067)	(0.063)
Observed controls' mean	3.235	3.644	3.694	3.584	3.203	3.623	3.665	3.572
School Fixed Effect	√	√	√	√	√	√	√	√
Controls	√	√	√	√	√	√	√	√
Adj. R^2	0.102	0.063	0.055	0.061	0.580	0.438	0.354	0.420
N	710	710	710	710	578	578	578	578

*p<0.1, **p<0.05, ***p<0.01.

Table 5: Results regarding non-cognitive skills. Note: The table presents estimates for $\beta_{1,h}, h = G, SSCS, CSE, CPI$ in equation (2). Standard errors, in parenthesis, are clustered at the class level.

6.2 Results on Secondary Outcomes

Attitude toward STEM subjects in schools

With regard to the attitude of students towards STEM subjects, the results using the two samples show two different scenarios. As we can see from Table 6, students in treated classes are more likely to show interest in STEM subjects. The measure we use is a standardized measure of the scale. Being in a treated class increases the measure by 0.22 standard deviation. We find similar results for self-declared average GPA. Despite being difficult to assess the importance of this intervention in improving GPA as self-declared, we believe the magnitude of the effect is non-negligible. Finally, we do not find evidence that students in treated classes like STEM subjects more. We cannot rule out that this effect masks some heterogeneity in the preference of students for different subjects categorized as STEM (e.g., students might like better computer science, rather than math or physics, which are all coded as STEM). Future analysis will investigate this possibility. Instead, using the matched sample, we cannot reject the hypothesis that none of the three measures is significantly different for students in treated classes. Controlling for baseline covariates seems to lower the estimated coefficient. As stated above, this can be either due to the correlation (by chance) of baseline covariates with treatment assignment or to a non-random mechanism of missingness of information that defines the two samples. Further investigations are needed to draw a more precise inference.

[30] For the sake of brevity, we do not report results' full tables, which, however, are available upon request.

	Full Sample			Matched Sample		
	$\tilde{Y}_{STEMSubj}$	$\tilde{Y}_{GPA}$	$Y_{FavSubjSTEM}$	$\tilde{Y}_{STEMSubj}$	$\tilde{Y}_{GPA}$	$Y_{FavSubjSTEM}$
$\hat{\beta}_1$	0.21*	0.21**	-0.04	0.15	0.06	-0.05
	(0.12)	(0.11)	(0.06)	(0.12)	(0.07)	(0.07)
Observed controls' mean			0.33			0.33
School FE	√	√	√	√	√	√
Controls	√	√	√	√	√	√
Adj. R^2	0.12	0.14	0.09	0.26	0.56	0.46
N	710	710	710	578	578	578

Table 6: Results regarding school outcomes. Note: Outcomes $\tilde{Y}_{STEMSubj}$ and $\tilde{Y}_{GPA}$ are the standardized versions of $Y_{STEMSubj}$ and Y_{GPA}, respectively. The table presents estimates for $\beta_{1,h}$, $h = STEMSubj, GPA, FavSubjSTEM$ in equation (2). Standard errors, in parenthesis, are clustered at the class level.

Attitude toward STEM careers at university

Finally, in Table 7, we try to give suggestive evidence on which channel is driving the results regarding university choices. Looking at the full sample, we cannot reject the null hypothesis that the interest and the ability in STEM careers at university were not impacted by the possibility of joining the courses. However, note that we estimate a positive coefficient for both measures. If restricting the sample, controlling for baseline values of interest and ability in STEM majors, we see that self-reported ability to undertake STEM careers at university is higher among students in treated classes (7 p.p., corresponding to a 17.5% increase). Future analysis will focus on investigating mechanisms more accurately.

	Full Sample		Matched Sample	
	$Y_{intSTEM}$	$Y_{confSTEM}$	$Y_{intSTEM}$	$Y_{confSTEM}$
$\hat{\beta}_1$	0.04	0.05	0.03	0.07**
	(0.04)	(0.04)	(0.04)	(0.03)
Observed controls' mean	0.33	0.32	0.33	0.32
School Fixed Effect	√	√	√	√
Controls	√	√	√	√
Adj. R^2	0.07	0.07	0.40	0.40
N	710	710	578	578
*p<0.1, **p<0.05, ***p<0.01.				

Table 7: Results regarding attitude toward STEM majors. Note: The table presents estimates for $\beta_{1,h}$, $h = intSTEM, confSTEM$ in equation (2). Standard errors, in parenthesis, are clustered at the class level.

7 Discussion and Concluding Remarks

In this study, we randomly expose Italian high school students from different majors to creative activities taught by FabLabs and assess the impact of this exposition on students' career aspirations, university choice, interest and confidence in STEM university courses, attitude towards STEM subjects, creativity, and grit. We find that exposure to the possibility of joining FabLab activities has overall a positive impact on all the variables assessed, except for career aspirations and creativity.

We find that students who are exposed to the possibility of joining the activities are more likely to express interest in enrolling to university and also to follow a STEM degree. Moreover, we show suggestive evidence that some of the mechanisms may be related to self-perceived ability in STEM subjects and change in some non-cognitive aspects (grit) of the individuals that may correlate with the intention to pursue a STEM career. We also show that students in treated classes are more likely to declare that they would not decide for a career as technical workers. Despite not being able to assess with precision which professions are more likely to be chosen, we argue that it is likely that part of them is deciding on a professional career in STEM.

The effects that we find from these preliminary analyses is likely to be diluted since we are estimating the effect of the *assignment* to FabLab courses (ITT); remind that a portion of students did not enroll in such courses although they were allowed to do so. A follow-up refined analysis will focus on the average effect of the treatment (ATE) and, even more specifically, on the effect for those who joined FabLab courses (ATT), for whom we expect to find a stronger positive effect.

Despite our analysis is likely to underestimate the impact of FabLab activities offered to high school students, we can already appreciate an overall positive effect on students' interests and attitude. More pilot projects should be encouraged to investigate how the making improves education, how it raises interest (especially that of girls) in STEM fields, how it can shape students' choices regarding higher education, how it can integrate students that do not conform with the current learning setting, and how making can be integrated into the national curricula. An interesting analysis by Samuelson and Brahms (2016), for example, finds that the success of bringing digital fabrication into the classroom relies heavily on the school's leadership, allocation of space, and integration with the existing curriculum. In doing so, Governments can rely on the network of FabLabs, makerspaces, and similar projects already active in their countries. These initiatives are a powerful source of lessons learned and can contribute to designing policies that respond to the idiosyncratic nature of the national educational curricula.

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