Evaluation and Program Planning 98 (2023) 102273

Contents lists available at ScienceDirect

Evaluation and Program Planning

journal homepage: www.elsevier.com/locate/evalprogplan

Online or on-campus? Analysing the effects of financial education on student knowledge gain

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A R T I C L E I N F O

JEL Classification:
G53
I21

Keywords:
Financial education
Experimental evaluation
Financial literacy
Online learning in Higher Education
Massive Open Online Course (MOOC)

A B S T R A C T

This paper describes the results of an experiment conducted in a technical university in Italy in 2019, involving the implementation and evaluation of an innovative short course on financial education. The programme applied a novel approach based on online learning and its effectiveness is compared against the effects of a traditional on-campus lecture, within an experimental setting. The findings indicate that the programme is effective: one week after taking the course, the students improved their pre-course test scores by about 4 points out of 10. No statistically significant difference in gains is found between students assigned to the online vs the on-campus mode of learning, suggesting a potential positive role of digital learning in this specific setting. An exploratory analysis of factors associated with the outcome reveal that the course has been particularly beneficial for those students initially less interested in finance.

1. Introduction

Financial literacy is currently considered one of the key competences for living in modern societies and economies (Remund, 2010). Several factors motivate people to acquire financial skills during their lifetime, among which the increasingly complex rules of financial markets, the diminishing role of public welfare services and the longer life expectancy (Lusardi & Mitchell, 2014). In such a context, individuals are called to make informed decisions about a number of issues that require, for instance, understanding how to save for the future, how to invest in a productive way, how to protect their own financial data and so forth. The positive effects of financial literacy at the aggregate level (i.e., economic and social returns, see Capuano & Ramsay, 2011) call for governments and institutions to take action to ensure that adequate levels of financial competence are acquired across the population as a whole (Hastings et al., 2013). Financial literacy can be improved through education. Triggered by the effort of several national and international agencies and governments to stimulate an increase in financial literacy, many financial educational initiatives are currently ongoing. However, investing in financial education is a worthwhile policy only as far as the effectiveness of the specific programmes can be demonstrated. Thus, each action should ideally be evaluated through robust statistical and econometric techniques, in order to establish the causal nexus between educational measures and gains in specific knowledge and skills. Moreover, while the number of educational interventions is growing significantly (see a synthesis in Walstad et al., 2017), there is still space for testing how these interventions should be designed to be highly effective.

This paper describes an educational initiative carried out in a leading university in Italy during the 2018/19 academic year, together with assessing the determinants of students' financial knowledge gain. A special feature of this programme is its use of an online learning platform to teach basic financial concepts. The main aim of this research experiment is to assess the effectiveness of a short course on financial education when it is conducted online or, instead, when it is taught through a traditional on-campus lecture. The target audience for the initiative consists of a cohort of first-year students taking a Business Economics course as part of their undergraduate degree in Mathematical Engineering. The specific course consists of a three-hour module on basic financial concepts, covering bank accounts, simple/compound interest rates, differences between shares and bonds, and loans and mortgages. Half the students attend a traditional lecture (on-campus), while the other half are provided with online lectures. The results highlight that both groups of students experience an increase in their knowledge of financial concepts, and that there are no statistically significant differences in the improvement between the two groups. This

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https://doi.org/10.1016/j.evalprogplan.2023.102273
Received 9 November 2021; Received in revised form 27 February 2023; Accepted 6 March 2023
Available online 9 March 2023

latter finding is encouraging and suggests that online learning is a viable instrument for delivering low-cost, effective, short programmes on financial education.

The present paper contributes to the current academic debate in two innovative ways. This is the first quasi-experimental evidence on the effectiveness of an online-in presence financial education initiative within an Italian university. Indeed, experimental evidence on the impact of financial literacy programmes is often limited to secondary education and do not specifically compare alternative modalities of delivery. In addition, this research explores the relative effectiveness of two different models for delivering the same content (online vs on-campus setting), underlining the importance of properly designing the specific interventions. In this perspective, this paper contributes to the (so far limited) stream of empirical literature that analyses the impact of online education on student knowledge gain, together with comparing two alternative teaching methods to deliver financial literacy concepts.

The paper is organised as follows. Section 2 provides a literature review about two important streams: (i) the effectiveness of financial education programmes and (ii) the effectiveness of online vs on-campus college education. Section 3 describes the experiment and the empirical analyses. Section 4 reports the main results, critically discussed. Section 5 concludes.

2. Previous literature

2.1. Effects of financial education programmes

The purpose of this section is to provide a short overview of some interesting studies where adequate econometric methods are used to test the effectiveness of financial education programmes. This part collects the most recent academic works – from 2010 to 2020 – and on those putting in place a Randomised Controlled Trial (RCT), with the aim of providing an overview of the methodologies adopted and the relative experimental designs, as a background to the experimental setting deployed in this study. The general effects of this kind of study are underlined by the meta-analysis of Kaiser and Menkhoff (2020), which states that generally financial education programmes enhance the skills of participants.

A first interesting example of a financial education project comes from Wisconsin, United States, at the Eau Claire elementary school. Batty et al. (2015) involve 4th and 5th grades pupils (9–11 years olds) from two school districts in a five weeks programme held by their own teachers and integrated into standard lessons. Each lesson lasted approximately 45 min and covered basic financial literacy, focusing particularly on saving and money management. Classes (randomly) allocated to the control group are able to take the financial education programme in the second term, after the conclusion of the experiment. The findings show significant improvements in the children's financial knowledge, suggesting that, to be effective, the topic should be integrated into the school programme.

A second study takes place in Brazil, involving approximately 25,000 high school pupils (Bruhn et al., 2016). The project reaches almost 900 schools and lasted 17 months; it is integrated into the normal school curricula and included classroom lessons and homework. The programme covers topics on basic finance and economics, introduced through many real cases connected to the students' daily life. Schools are assigned to the treatment or control groups according to a matched stratified randomisation. This programme is considered successful on many dimensions, showing significant improvements in the students' financial skillsets, although with controversial effects on actual behaviours.

A more recent programme in Spain involves around 3,000 9th and 10th grade pupils (13–16 years old) from 78 high schools (Bover et al., 2018). The programme starts in 2014–15 with a 10-h course integrated into the school curriculum, so student participation is mandatory. The course covers basic financial topics, such as saving and interest, risk and budgeting, types of bank accounts, pension funds and insurance investments. Randomisation is conducted within the schools. The evaluation shows that financial knowledge becomes more homogeneous across students in state schools after they take the course, with a significant increase in knowledge observed among at-risk students, that is, those more at risk of dropping out or who are repeating the year. The analysis does not suggest that financial education also improves the students' inter-temporal decision-making.

Becchetti et al. (2013) conduct a randomised evaluation of a financial education project held in Italian high schools in Rome and Milan. The project involves more than 900 students in 36 classes from academic and vocational high schools (*licei*, technical schools and professional schools). The students take a three-month course on financial and economic basic notions over a total of 16 h inserted within their standard lessons, so the course is considered to be mandatory. The teachers are provided with standardised material as support to teaching and to be distributed to students. The findings suggest that this short basic financial education course significantly affects the learning process in specific student subgroups (e.g., girls, academically poor performers, students not intending to go to university), showing that progress in financial literacy is greater among the categories with poor *ex ante* notions of personal finance.

In a case study from Singapore, Barua et al. (2018) make use of a one-semester university course dealing with the use of money (for example, savings) and asset management to test its effectiveness on the students' saving behaviour. To the best of our knowledge, this is the only systematic evaluation of a financial education programme conducted in universities through RCT and published in an academic journal over the past few years. Due to the particular selection of students, the evaluation results in an imperfect randomisation. The researchers collect data from a baseline survey before starting the course and from a post-test on financial knowledge and behaviour at the end. Then information is analysed through a difference-in-differences approach that takes into account the students' starting point knowledge before the treatment (financial education course). The findings show that the course produces improvements to the students' financial knowledge (+ 11 % in score) and financial planning (+ 16 %).

The five works analysed in this section reveal some common patterns. First, the students' motivation in terms of actively joining financial education programmes has to be taken into consideration. In this vein, these initiatives must be inserted within ordinary educational programmes, so that students – if they are not interested in the subject – are at least motivated by a potential good mark. Second, the initiatives are designed to be on a voluntary-based participation, which affects the effectiveness of the evaluation by attracting participants who self-select themselves due to their interest or weakness in financial literacy (selection bias). Third, adequate randomisation needs to be assured in advance when testing the effectiveness of financial education programmes, allowing for robust estimates of the effects.

In recent years, most experiments have been conducted in schools, while no convincing experiments are still reported in the area of Higher Education Institutions (HEIs), especially regarding online teaching: the present research aims at filling this gap. While there are a few studies concerned with interesting financial education modules for students in universities/colleges (Brugiavini et al., 2020; Borden et al., 2008; Cude et al., 2013; Gross et al., 2005; Harcourt-Cooke et al., 2022; Peng et al., 2007; Xiao et al., 2014), they are not conducted using randomised control trials, nor test the effectiveness of alternative delivery modes.

In summary, this section gives an overview of the main experimental approaches and relative main findings. As also confirmed by the meta-analysis of Kaiser and Menkhoff (2020) and Kaiser et al. (2022), the overall effects of financial education programmes (tested through Random Controlled Trials) may be considered effective to improve financial knowledge of students. Even though, the effects gained from these initiatives can be considered encouraging, it is difficult to draw general conclusions about effectiveness from one study or programme.

For this reason, it is necessary to get robust evidence involving a larger number of initiatives and financial education projects – a goal that the present work pursues.

2.2. The effectiveness of online educational programmes

In addition to the aspects described in Section 2.1 on the effects of financial education programmes, the present research adds an important component testing the effectiveness of alternative forms of teaching, namely in a classroom setting vs via an online platform. In recent years, a growing body of literature has assessed whether providing online education can compete with traditional teaching in terms of bestowing the same achievement gains, especially in higher education.

The first robust experimental evidence on the effect of online education on student achievement comes from Figlio et al. (2013). In a class on Principles of Microeconomics at a US state university, students are randomly assigned to one (live, in presence) or other (online only) teaching mode. No statistically significant difference is observed regarding student achievement when considering the overall sample of nearly 300 students. Nevertheless, the effect is heterogeneous in terms of ethnicity, gender and ability level, as online teaching is found to be detrimental for hispanic, male and low-ability students, who recorded a 3.5–11.3 % drop in score compared to students attending traditional classroom settings. Bowen et al. (2014) expanded a similar experiment with the randomisation to six US campuses and found no statistically significant difference between in-presence and blended formats, the latter involving mixing online teaching with a one-hour-long live lecture a week. Across the 600 students attending the courses on statistics, the difference between the two teaching methods is not statistically significant either in terms of success rates or in terms of student achievement, regardless of any personal feature characteristic that could affect the functioning of the programme. Joyce et al. (2015) further contributed by randomly placing 725 students at a US state university in either a traditional or a "compressed" class on Introductory Microeconomics, where – in the latter case – a weekly lecture replaced the standard twice-a-week format. The same online material is provided to both classes. A sort of "substitution effect" (i.e., focus on videos replacing traditional lectures) is observed in the compressed class, where students watched videos more frequently than in the traditional format. The effect on student achievement is mixed, given that the grades in the mid-term exam taken by students in the traditional format lectures are 0.21 standard deviations higher than those in the compressed format, although the difference is not statistically significant in the final marks. Alpert et al. (2016) compared three delivery modes by randomly assigning students to a traditional, blended (a mix of online and live teaching lectures) or online-only class on Economics Principles in a US university. The results showed that the students attending the online sessions performed 5–10 points worse than those in the traditional format, while there is no significant difference for the blended format. Low-ability students performed worse when assigned to the blended or to the online format teaching, meaning that blended education can still be detrimental for specific subgroups of students.

Whilst all the examples come from the US, Cacault et al. (2019) has recently provided empirical evidence on the take-up and effect of live video streaming at the University of Geneva (Switzerland). In their experiment, first-year undergraduate students are randomly offered access to a live video streaming platform for eight of their compulsory courses. In addition, the streaming sessions of the weekly traditional lectures are also made available at random, so that around 23,000 combinations of student-course-week observations are collected over two terms. The study adds evidence about the use of online material by students. The results showed that the take-up level is relatively low, as only 10 % of the students used the streaming service when available, and this occur mostly in case of unexpected events (like bad weather conditions), i.e., the cost of attending live lecture is particularly high. By triangulating economic theory and results, the authors revealed that, for high-ability students, the proper counterfactual is no-attendance and the effect of streaming the lectures is positive, up to a 2.5 % increase in their exam grades. For low-ability students, class attendance is the most convenient counterfactual and the negative effect amounted to a 2 % decrease in their exam grade.

Summarising, limited robust experimental evidence is available on the use of online education in HEIs. The available evidence shows a null or negative effect for online education (on student achievement) in comparison with traditional learning modes. However, the difference between traditional and blended learning is non-significant or slightly in favour of the latter. The heterogeneity of the outcome is significant; specifically, the lack of person-to-person interaction is particularly detrimental for low-ability students, who instead benefit the most from classroom lectures.

The need of understanding whether and how financial education may be taught in an online setting is the interception of the two literature streams reviewed above. Indeed, considering the complex mechanisms driving financial knowledge, there is the urgency to test different modalities of teaching. The key issue to be addressed is provided by the relative effectiveness of traditional in-person and online lectures. Some efforts have already been spent to test whether an online financial education programme affects the knowledge of students (Aljamal et al., 2015; Batu et al., 2018; Biktimirov & Klassen, 2008). In some papers the contribution to students' financial knowledge of the two different modalities of lecture is investigated without putting in place a randomised experiment (Flannery et al., 2013; Grinder, 2014; Kennelly et al., 2011; Scheiding, 2015). Despite the limited evidence, previous studies demonstrate a comparable level of effectiveness between online and in-person format or, in limited cases, a larger positive effect of online lectures in raising students' knowledge on financial topics.

The present study is positioned at the midway between financial education and online learning. Specifically, the present paper contributes to the effectiveness of online financial education programmes by deploying a rigorous experiment in a higher education setting.

3. Methodological approach: the experimental design

3.1. A description of the experimental setting

The quasi-experiment is set in a leading Italian university, specialised in Engineering, Architecture and Industrial Design. The opportunity for the experiment is provided by the Department of Mathematics having developed a Massive Open Online Course (MOOC) on financial basics for university students, in collaboration with the university Learning Innovation Lab. The MOOC is now uploaded on the University portal reserved for web lectures, and provides the ground for the experiment covered in the paper.

The experiment considers first-year students taking an undergraduate degree course in Mathematical Engineering at the University as subjects of the analysis. The specific course in question is the first-year mandatory course in Business Economics held in the spring term of 2019. The course has been expanded to include, alongside normal course scheduling, a lecture on basic financial matters, which provides the material for the experiment. Given the large number of students taking the degree course in Mathematical Engineering, the University opted to divide students into two classes based on first letter of last name (A–L in the first group, M–Z in the other). This assignment allows to conduct a natural experiment to test whether the teaching method affects the effectiveness of the financial education course, as one class is assigned to the on-campus session and the other one to the online session. It is worth noting that a control group, strictly intended (i.e. not taking the financial literacy course), is not settled, as the objective is to compare the two teaching methods and not the effectiveness of the programme itself. The comparability of the exercise for the two classes is ensured by that the same professor teaches both types of course: on one hand the professor teaches on-campus in a traditional way, on the other

– in the online course – he plays in animated interactive videos. The videos are organised as follows: different characters present their ordinary financial problems, then the professor interacts with them explaining how to face that situation providing key finance notions. A total of 403 students take part in the project, divided into two classes of 226 and 177 students, respectively. The first class is assigned to online treatment involving the MOOC-based lecture, while the second class attends the on-campus lecture held during the timetable of Business Economics course.

The experiment is structured following three steps: pre-testing, training and post-testing. The aim of the pre-testing phase is to capture the participants' initial financial literacy level, together with assessing their baseline attitudes in terms of financial trust, spending habits and interest/competency in financial topics (Annex B includes the questionnaire used in this phase). Students do not have access to their pre-test, nor their results, until the end of the experiment, so they have no incentive to restudy the topics covered by the first assessment. All students fill the survey at the beginning of a lecture on Business Economics and then the two classes split, with the on-campus class attending the lecture on basic financial topics held by the professor from the University's Department of Mathematics, and the other class follows a lecture on Business Economics. In a second moment, the online-only class is required to sign up for the MOOC on basic finance and attend, in particular, the module dealing with bank accounts and interest rates, bonds and stocks, investments and mortgages that contains the topics covered in the on-campus class. The third step involves post-testing, which is carried out one week after the pre-test: at this stage students are asked to complete a test on the topics taught in the lecture/videos. The structure of this second assessment is organised in a way pretty different from the first one since the goal is to ascertain the improvement in financial education. The students fill this test during a Business Economics lecture, simultaneously in the two classes. Hence, the test modality ensures that the professors and teaching assistants are able to exert a high level of control, minimising any cheating opportunities.

It is relevant to mention some details of the course environment. Students are not required to attend the Business Economics lectures (and their presence is not checked systematically), but the University's recommendation is for them to do so, and therefore attendance is in general high, on average around 80 % of the students of the course. For this reason, authors are quite confident to reach the majority of enroled students. Also, students do not know that they are taking part in an experiment, so their only motivation for taking both tests is of gaining one extra point in the end-of-course exam (explicit incentive). Indeed, students who answer 50 % or more questions correctly in the post-test receive an extra point added to their Business Economics final grade (on a 30-point scale). The attrition rate is not possible to assess because University gives access to information for only those students participating in the experiment.

By checking attendance on the online platform, it is possible to assess whether students assigned to the online class actually attended the online videos. On the same principle, students assigned to the on-campus class and have also access to the online platform can be detected. Thus, there are two potential types of non-compliant students: (i) those who should have watched the MOOC videos but did not, and (ii) those who are requested to attend the live lectures only, but who also register on the MOOC, receiving, therefore, a kind of double treatment. Later in the paper, a precise description of how this research deals with non-compliant students will be given.

Spillover effects cannot be completely ruled out, for instance the possibility that students may discuss about the course, or maybe share their teaching notes between the two classes or cheat during the tests. A series of precautions have been adopted to minimise this possibility. First, both tests are held simultaneously in the two classes, with strong supervision about possible cheating. Secondly, the topics covered by the course are the same in the two treatments, so even if they pass their notes each other, this does not represent a source of major alteration of the experiment's validity. Lastly, students assigned to on-campus group may be suggested by their class counterparts to watch videos on MOOC platform, but by checking accesses this eventuality can be controlled (while share of notes from the on-campus lesson is more difficult to be checked).

Alongside the participants' test scores and the data on their attitude towards finance collected from the surveys, additional relevant information is obtained from the University's administration office (the complete variables' list and their description is presented in Table 1). Data are supplied and treated in a completely anonymised manner according to European GDPR rules. The data used in the analyses relate to (i) *educational career information*, such as the students entrance test scores, their GPA (Grade Point Average, i.e., their average grade for individual courses/modules weighted by the number of credits associated to each course/module), the credits obtained before taking the course and the exams they did (independently of the outcome) before taking the course and (ii) *individual characteristics*, such as gender, nationality, socio-economic status (SES) and secondary schooling (vocational or academic).

3.2. The financial education programme

"*Finanza per tutti*" ("Finance for All") is a MOOC offered in Italian since 2017, available for free on the University's dedicated online platform. Targeting the general public, the aim of the course is to teach the basic concepts of financial literacy, starting from daily problems, such as, for example, how to get a mortgage, how to invest wealth, how to choose a bank account, etc.

The course is divided into three main blocks. The first block deals with bank accounts, simple/compound interest rates, differences between shares and bonds, and loan and mortgage repayment. The second block covers financial risks, insurance and investment decisions, and behavioural finance, highlighting the most common investment mistakes. The third block deals with advanced financial products, including options and swaps, providing also a guidance to the legislation protecting investors. Each block contains several videos, each lasting about eight minutes; all the videos are designed as a discussion between an

Table 1
Variables' description.

Variable	Description
Individual characteristics	
Deviation from standard age	Difference b/w student's expected age (e.g. 19 or 20 year olds) and actual age.
SES (Index of socio-economic status)	Socio Economic Status of the student based on university fees contribution (from 0 to 10)
Male (dummy = 1)	If student is male = 1, 0 otherwise
Off-site student (dummy = 1)	If student is off-site (e.g. he/she moved to university's city to study) = 1, 0 otherwise
Part-time working student	If student has a part-time work = 1, 0 otherwise
Full-time working student	If student has a full-time work = 1, 0 otherwise
Individual attitudes and beliefs about finance	
Not interested (from PCA)	See PCA analysis
Risk prone (from PCA)	See PCA analysis
Cardholders (from PCA)	See PCA analysis
Educational career information	
GPA in the 1st semester	Student's average grade weighted on the associated credits (e.g. ECS)
Credits in the 1st semester	Total credits the student earned
Admission test score	Score student obtained at university admission test (from 60 to 100)
Scientific high school	If student comes from a Scientific High school = 1, 0 otherwise
No-show exam rate	if the student never showed up to any exam = 1, 0 otherwise
Results from finance tests	
Pre-test score	Student's score obtained in the pre-test (from 0 to 1)
Post-test score	Student's score obtained in the post-test (from 0 to 1)
Delta (Post-Pre test)	Difference in student's score b/w pre and post tests

animated character (with a problem to be solved) and a professor.

The quasi-experiment described in this paper uses seven videos selected from the first block, meaning that it is akin to a “basic” course on personal finance. The specific content of the videos is the following: (a) time and interest rates (the difference between simple and compound interest); (b) interest rates and the time horizon (dealing with annual, semi-annual and quarterly interest rates); (c) bonds and ratings (internal rate of return for a coupon bond, spread and ratings of corporate and government bonds); (d) market interest rate curves and their relationship with bond prices; (e) loans (internal rate of return, annual percentage rate and nominal interest rate); (f) mortgages/loans repayment calculation (how to calculate interests in a fixed interest rate framework). It must be revelled here that students are attending a course in Business Economics altogether, so they are at least partially exposed to some of these economic and financial concepts.

The scheduled lesson lasts about three hours in the live class format, while the online class watches a combination of videos lasting about 55 min. This time difference between classes is justified by the diverse teaching impact and attention level of the two settings, implying a proportion of 1:3 h between online and on-campus teaching hours.

3.3. Data

From the 403 students enroled in the two classes, a total of 365 students attend both pre- and post-tests. Of these, 158 are assigned to the on-campus class and 207 to the online-only class, with a retention rate (computed as the number of students participating in the experiment over the number of students formally enroled) above 90 %. Subsequent analysis will take into consideration non-compliant students, too. The term “non-compliance” is used when a student does not follow the treatment’s assignment. Hence, in addition to the online-only compliers (n = 181) and the on-campus compliers (n = 114), non-compliers are labelled as (i) no treatment (n = 17) when students assigned to the online class do not take the MOOC, and (ii) double treatment (n = 28) when the students assigned to the on-campus class also take the MOOC.

In addition to the results of the tests on financial literacy, the dataset also contains demographic and performance data. In particular, information on age, gender, whether students come from another city (i.e., outside Milan) or not, if they have a part-time or a full-time job, the type of secondary school they attended and their socio-economic status. This last piece of information is derived from each student’s tuition fee band, which in turn is determined on the basis of family income. The tuition fee band goes from 0 (exemption from tuition fees) to 10 (maximum level of tuition fees). In addition, information about performance of all the students are collected, including their GPA on a scale from 18 (the minimum pass grade) to 30, their total credits (CFUs) received in the first semester (students are first-year students), their admission test score (on a 0–100 scale) and their no-show exam rate (noting that students can re-sit exams). The rate is calculated as the percentage of the student’s absenteeism per exam, this indicator measures how many times the student is “absent” on the day of the exam, providing a proxy for each student’s academic readiness. The baseline descriptive statistics are provided in Table 2.

Data reveal that there are no structural differences between students assigned to the online-only class and those to the on-campus one. This is evident by the high p-values from t test in Table 2, which compares variables’ means by group. To further prove the groups’ balance, Table C (in Annex) resumes the results from a logit regression which adopts as dependent variable the group’s assignment to check the variables’ significance. Here, only some academic performance variables suggest differences by groups, probably due to the heterogeneous (and short) teaching path among classes. In fact, academic information relates only to the first semester of the first year, which comprises three mandatory courses, so the teacher-specific effect may disclose initial differences.

On a descriptive perspective, both groups include 60 % male students and the average socio-economic index is 6 (out of 10). About 40 % of the students are off-site, 16 % work part time, while less than 1 % work full time – although it is important to note that there could be a higher proportion of students working full time in the potential target population, but they would not be in class during the experiment. When looking at performance in the first semester, the students obtained between 19 and 20 credits on average (out of a maximum of 30). Both groups scored on average 74 (out of 100) in the admission test, and more than 80 % attended a STEM-focused high school (*liceo scientifico*). The no-show exam rate is between 5 % and 8 %. The only statistical difference between the two groups of students is provided by their average GPA for the first semester, which is 20.6 for the online course students and 22.8 for the on-campus course students. The picture that emerges from the analysis of these statistics is that randomisation, determined on the basis of the students’ last name, appropriately works. This is confirmed by a statistical test rejecting the difference of the average students’ features for the two groups (online vs on-campus).

Principal Component Analysis (PCA) classifies students into archetypes on the basis of the students’ answers to the questionnaire concerning their beliefs and attitudes. The aim of this procedure is to model the potential effect of treatment due to initial attitudes of the students. The first three components are selected, where each of them shows an eigenvalue greater than one and altogether they explain more than 50 % of the total variance. To better interpret the results, the component

Table 2
Descriptive statistics relating to the students’ characteristics and their pre and post test results.

Variables	Online group N = 207	On-campus group N = 158	t-test (p-value)
Individual characteristics			
Deviation from standard age	0.035 (0.234)	0.035 (0.402)	0.997
SES (Index of socio-economic status)	6.106 (3.392)	6.092 (3.443)	0.969
Male (dummy = 1)	0.606 (0.490)	0.627 (0.485)	0.699
Off-site student (dummy = 1)	0.379 (0.486)	0.418 (0.495)	0.463
Part-time working student	0.167 (0.374)	0.169 (0.376)	0.813
Full-time working student	0.005 (0.071)	0.007 (0.084)	0.954
Individual attitudes and beliefs about finance			
Not interested (from PCA)	-0.008 (0.998)	0.011 (1.006)	0.869
Risk prone (from PCA)	0.059 (0.994)	-0.082 (1.006)	0.203
Cardholders (from PCA)	0.033 (1.028)	-0.047 (0.961)	0.567
Academic performance and results			
GPA in the 1st semester	20.664 (8.862)	22.832 (6.644)	0.010
Credits in the 1st semester	19.253 (14.310)	20.268 (12.047)	0.479
Admission test score	74.631 (9.943)	73.59 (9.489)	0.332
Scientific high school	0.904 (0.295)	0.817 (0.388)	-
No-show exam rate	0.083 (0.19)	0.057 (0.169)	0.188
Results from finance tests			
Pre-test score	0.516 (0.211)	0.527 (0.194)	0.621
Post-test score	0.911 (0.095)	0.935 (0.114)	0.036
Delta (Post – Pre test)	0.395 (0.232)	0.408 (0.226)	0.611

Notes. For the definition and description of the variables, please refer to Section 3.3 of the paper. The Table refers to treatment’s assignment, not considering whether the student is compliant or not.

loadings allow to identify three groups (archetypes) of students. The corresponding coefficients for the variables are reported in Table 3. The first group of students is labelled as "not interested", on the basis of the most important component loadings: negative interest in financial topics (− 0.552), agreement with the idea that they will never find financial topics interesting (0.564), yet, at the same time, an ability to handle financial concepts, once studied them (0.557). The second group consists of "risk-averse" students, for these students the risks associated with financial investments are unmanageable (− 0.649), they also think that it is necessary to acquire a lot of information before making any financial decision (0.682). The third archetype of students consists of the "card-holders", in this case, the most important component loadings are holding a bank account (0.488) and a credit card (0.529), as well as making use of the credit card itself (0.489), these students can be considered as financially-active. As explained later in more detail, for each student, the values of the three components are standardised and embedded in the econometric models as explanatory variables, with the goal of capturing the association between students' financial attitudes/behaviour and their results in the financial literacy test (both ex-ante and ex-post).

3.4. Econometric and statistical specifications

The empirical analysis is conducted by mixing two main methodological approaches. The baseline results are derived through an ordinary least squares (OLS) regression on the experimental data. Specifically, the evaluation considers the Average Treatment on Treated (ATT), defined as the effect calculated for the individuals who are actually treated (i.e., those who attend the online course after being assigned to it). These baseline results are also supplemented by a model that uses Instrumental Variables (IV) to test for their robustness. In addition to the baseline estimates, Machine Learning (ML) algorithms are employed to search for potential heterogeneity on the treatment effect. As pointed out by Schiltz et al. (2018), the methodologies in the ML family are particularly well suited to situations where the relationships between influencing factors and the outcome of interest (in this case, the financial literacy test score) are highly nonlinear and interact with the individuals' characteristics. Specifically, Regression Trees (RT) and Random Forests (RF) are implemented in order to study the effect of the financial education initiative on different sub-populations of students.

Table 3
Principal Component Analysis on the variables relating to financial attitudes at student-level, and clustering of the student archetypes.

Variable	Component 1: 'not interested'	Component 2: 'risk-averse'	Component 3: 'card holder'
I have a bank account	0.028	0.222	**0.488**
I have a credit card	0.03	0.193	**0.529**
I frequently use the credit card	-0.163	0.128	**0.489**
I have a mortgage or funding	-0.03	0.067	0.155
I read/listen to economic news on a regular basis	-0.177	-0.017	-0.286
Making financial operations implies taking manageable risks	-0.013	**-0.649**	0.295
Financial knowledge is relevant for making proper choices	0.046	**0.682**	-0.153
Only those who studied finance should make financial transactions	-0.04	-0.021	-0.133
It is better not to trust financial market operators	-0.053	-0.058	-0.092
I am interested in financial topics	**-0.552**	0.019	0.026
I will never be able to cope with financial matters	**0.564**	-0.025	0.017
Once you get the right information, you can deal with financial matters	**0.557**	-0.019	0.017

Notes. Component loadings are reported. Values in bold refer to the variables most representative for each component, being the highest in absolute value. The results are obtained by means of a Principal Component Analysis.

3.4.1. Econometric methods – analysing the results of the experiment

The first estimation is computed with OLS regression on the pre-test scores to determine the covariates that predict the students' initial performance. The model can be expressed as follows (Eq. (1)):

$$y_{PRE_i} = \beta_0 + \beta_1 X_{1_i} + \beta_2 TREAT_i + \varepsilon_i \quad (1)$$

where, for the *i-th* student, the dependent variable y_{PRE_i} is regressed against a set of student level covariates X_{1_i} related to their individual characteristics, academic ability and relative attitude towards finance. This latter dimension consists of the component loadings resulting from the PCA described in Section 3.3. Finally, the randomised assignment of students to the treatment is controlled adding $TREAT_i$, a dummy variable equal to 1 when the student is assigned to the online delivery mode and 0 otherwise. Given the surname's first-letter assignment, this variable is expected to be non-significant in this regression.

The second model is designed to capture the treatment effect by means of the following OLS regression (Eq. (2)):

$$\Delta_{POST-PRE_i} = \beta_0 + \beta_1 X_{1_i} + \beta_2 C\_TREAT_i + \beta_3 NOTREAT_i + \beta_4 DOUBLETREAT_i + \varepsilon_i \quad (2)$$

where the response variable accounts for the difference between the post- and the pre-test, both measured on a 10-points scale, while the student level covariates (X_{1_i}) are the same as those mentioned in Eq. (1). The key variable is here represented by C_TREAT_i which indicates whether a student assigned to the online treatment (he complies with it - 1 - and 0 otherwise). Given the existence of a small group of non-compliant students, as described in Section 3.3, it is controlled for them through the dummy variables $NOTREAT_i$ and $DOUBLETREAT_i$. The first variable identifies students in the on-campus group, while the second variable refers to students in the double treatment group. Hence, the reference category for the results is that of students who are assigned to the on-campus group and indeed attend the on-campus class. In addition, a third model is developed where only compliant students are considered, hence measuring the "pure" effect of the treatment on the treated.

Finally, given that the presence of non-compliant students may lead to selection issues, the treatment effect is also estimated by means of a two-stage-least-square (2SLS) Instrumental Variable (IV) approach. The instrument should be a variable related to the treatment but unrelated to the outcome, in order to identify an unbiased treatment effect. In this case, the random assignment of students to the online or on-campus group represents a good instrument as random by definition, and hence it is used to estimate the first stage regression as follows:

$$C\_TREAT_i = \alpha_0 + \alpha_1 X_{1_i} + \alpha_2 TREAT_i + \varepsilon_i \quad (3)$$

where the endogenous output variable C_TREAT_i is regressed against the full set of covariates X_1 plus the instrument $TREAT$. Then, the fitted values are used in the second stage regression:

$$\Delta_{POST-PRE_i} = \beta_0 + \beta_1 X_{1_i} + \beta_2 \widehat{C\_TREAT}_i + \varepsilon_i \quad (4)$$

where the final output variable $\Delta_{POST-PRE_i}$ is estimated against the vector of student level covariates and the fitted values of C_TREAT, i.e., the values of the variable of interest as obtained through the first stage regression.

3.4.2. Machine learning techniques: a further step to investigate the results of the experiment

A Regression Tree (RT) is implemented, where the basic idea is to relax the linearity of the relationships between variables, as implied by the model implementing a non-parametric statistical procedure. More precisely, regression trees are decision trees where the target (dependent) variable take continuous values, in contrast with classification tree where the target variable is discrete. In this case, as the delta in pre-post test scores (post-test values minus pre-test values) is a continuous variable, Regression Tree is adopted. The goal of decision trees is to identify mutually exclusive subgroups of the population whose members share common characteristics that influence the dependent variable, so, in this case, the difference in the students' score between their pre- and post-tests.

In general, decision tree algorithms begin with one "node" or group that contains the entire sample and is called "parent node". The procedure then examines all possible independent variables and selects the one that maximise the homogeneity of the dependent variable within two subsets. More precisely, dealing with regression trees, we used the Mean Squared Error (MSE) to measure homogeneity: for each independent variable, the algorithm picks up a threshold to divide the sample in two subsamples (e.g., elements of the sample having the independent variable value smaller/larger or equal than the threshold), and compute the MSE of the two subsamples. Once it finds the independent variable and the threshold which minimise the MSE of the two subsamples, it splits the parent node accordingly in two descendent nodes. Again, within these two nodes, the tree-growing methodology continues by assessing each of the remaining independent variables and choosing the one that is the most suited for the splitting procedure. When the process stops, and the tree is therefore pruned, the leaf nodes contain subgroups with homogeneous characteristics. According to this methodology, the leaf node shows the average improvement in score (the post- and pre-test delta) among the students belonging to that node (Lemon et al., 2003). Mathematical details about the method are described in the Annex A to the paper.

A Random Forest (RT) is an ensemble predictor based on multiple regression trees. Basically, a Random Forest takes a set of individual decision trees and, for each one, it only considers a subset of predictors as split candidates (Breiman, 1996, 2001; Schiltz et al., 2018). The main difference is that, with the methodologies described above (the construction of a single decision tree), all the predictors are considered at each split, yielding that often "weak" predictors are not considered, and therefore it is impossible to measure their impact. With Random Forests, by only considering a subset of variables at each split, different trees are obtained and then averaged. The result shows the ranking of the highest scoring classes in regression trees (Shi & Horvath, 2006).

4. Results from the empirical analysis

4.1. Determinants of pre-test scores

Before assessing the effect of a student taking the financial education programme online rather than attending a live lecture, the attention is on the determinants of the scores obtained by the students in the pre-test, i.e., before implementing the education programme. The results are reported in column (a) of Table 4. First, it is clear that no differences emerge in pre-test scores between the students assigned to the different treatments (online vs on-campus). As expected, the (quasi-random) assignment to online or on-campus course does not reveal any difference in the pre-test score, corroborating the validity of the experiment. Two student features are associated with the pre-test score. Male students score higher values than female students, confirming a gender bias typical of the financial literacy of young people in Italy, as well as in a number of other countries (see Fonseca et al., 2012). In addition, students who have full-time jobs are, on average, more financially educated than those who do not, notably because they are more exposed to financial matters in their life and work. In any case, it is important to point out that these students represent less than 1 % of the overall sample (so they are 4 or 5 people). When considering the students' attitudes and beliefs, the pre-test scores are unsurprisingly lower for the students labelled as "not interested" (group 1), and higher for students

Table 4
Results from the econometric analysis – the effects of the educational programme on student scores in their financial literacy test.

	Factors associated with pre-test scores (a)	Model 1 Delta (Post – Pre test) *with non-compliers* (b)	Model 2 Delta (Post – Pre test) *without non-compliers* (c)	Model 3 Delta (Post–Pre test) *with non-compliers*, Instrumental variables (d)
Treatment - course attended online	-0.006 (0.022)	-0.025 (0.027)	-0.029 (0.026)	
Treatment - course attended online Fitted (Second Stage)				-0.020 (0.027)
Deviation from standard age	0.005 (0.037)	-0.065 (0.042)	-0.060 (0.041)	-0.064 (0.042)
SES (Index of socio-economic status)	0.001 (0.003)	-0.001 (0.004)	0.001 (0.004)	-0.002 (0.004)
Male (dummy = 1)	0.072*** (0.022)	-0.084*** (0.025)	-0.083*** (0.026)	-0.084*** (0.025)
Off-site student (dummy = 1)	-0.030 (0.023)	0.019 (0.026)	0.034 (0.027)	0.019 (0.026)
Part-time working student	0.009 (0.029)	0.009 (0.033)	0.014 (0.036)	0.007 (0.033)
Full-time working student	0.360*** (0.139)	-0.294* (0.159)	-0.244 (0.154)	-0.293* (0.159)
Not interested (from PCA)	-0.047*** (0.011)	0.041*** (0.012)	0.024*** (0.0013)	0.041*** (0.012)
Risk-prone (from PCA)	0.003 (0.011)	-0.002 (0.0012)	0.010 (0.012)	-0.002 (0.012)
Cardholders (from PCA)	0.020* (0.011)	-0.028** (0.012)	-0.017 (0.012)	-0.028** (0.012)
GPA	0.004** (0.002)	-0.004* (0.002)	-0.004* (0.002)	-0.004* (0.002)
Credits acquired in the 1st semester	0.0004 (0.001)	0.0003 (0.001)	0.001 (0.001)	0.0003 (0.001)
Admission test score	0.003** (0.001)	-0.003* (0.001)	-0.002* (0.001)	-0.003* (0.001)
Scientific high school	-0.040 (0.034)	0.076* (0.039)	0.087** (0.040)	0.075* (0.039)
No-show exam rate	0.031 (0.073)	-0.002 (0.083)	0.017 (0.085)	-0.001 (0.083)
No treatment *(non-compliers)*		0.003 (0.056)		
Double treatment *(non-compliers)*		-0.030 (0.046)		
Constant	0.191** (0.092)	0.691*** (0.106)	0.627*** (0.110)	0.684*** (0.105)
Observations	335	335	290	335
R-squared	0.189	0.161	0.165	0.160

Note: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

labelled as "cardholders" (group 3). Academic ability matters for financial literacy measured before the educational initiative: both the admission test scores and the GPA in the first semester is positively associated with higher pre-test score.

4.2. Baseline results: descriptive and causal evidence

The density distribution of the gains in test scores of students assigned to the online or the on-campus group are shown in Fig. 1. Notice that in this analysis it is considered the increase (e.g. gain) in test scores between pre- and post-treatment as dependent variable. In other words, the main interest is not in analysing the determinants of financial literacy scores at the end of the programme, while instead it is in focusing on the factors associated with an *increase* in test scores after the implementation of the programme. Fig. 1 shows, at least descriptively, how the course, in both formats, improves students' financial literacy, highlighting an average improvement of around 50 % of correct answers for both classes. Further, the two distributions quite overlap, suggesting not being statistically different. This latter consideration is confirmed by the *p-value* resulting from a non-parametric Kolmogorov-Smirnov test around 0.9, bringing to accept the null hypothesis of equality of the two distributions.

The main findings of the analysis are reported in columns (b) and (c) of Table 4. Model 1 (column b) and Model 2 (column c) differ because the former includes control variables to check for non-compliant students, while they are excluded from the empirical analysis in the latter. The findings are robust and are very similar across the two models.

Two main features of the students associated with an increase in financial literacy: gender and full-time employment. Compared to female students and students who are unemployed, male students and students with full-time jobs experience lower gains in the test scores. Interestingly, these are the two groups of students who achieved higher scores in the pre-test. A possible interpretation of this negative association between pre-test scores and gains is that the students in question are already skilled in the financial field and so they do not benefit from the basic programme proposed in the experiment. It could also be the case that these students underestimate the complexity of some basic financial concepts and do not put enough effort in studying the lecture/videos proposed in the experiment. In the same vein, it is also interesting to observe that "cardholder" students (group 3) benefit in a more limited way from the programme, again probably because they already have a good basic knowledge. All else being equal, these students improve less in their financial competency than similar students who were less interested or risk averse. Students who are deemed to be "not interested" (group 1) experience, on the contrary, a statistically significant positive benefit from attending the financial education programme. These results confirm the claim that financial education programmes (at least, those teaching basic concepts) can have a stronger effect on students endowed with little initial financial knowledge and may provide less benefit to people already skilled in this field.

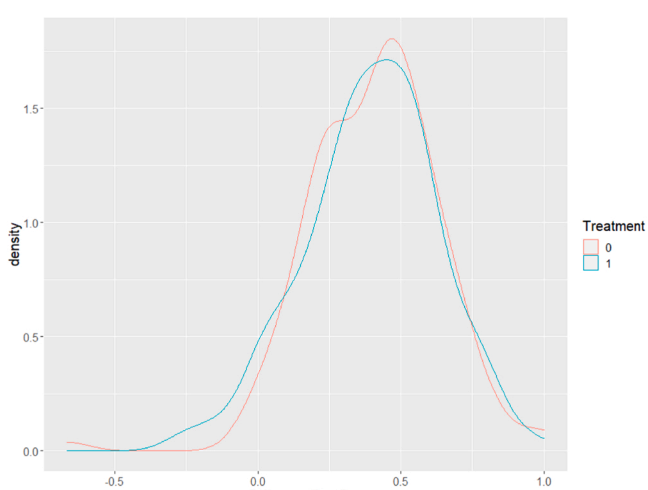

Fig. 1. Density distribution of the outcome (delta score between pre and post test) of students assigned to the online group (= 1) and to the on-campus group (= 0). Note: The density distributions are approximated through a Kernel function. To test whether the two distributions are statistically different, the Kolmogorov-Smirnov test is computed, resulting with p-value = 0.9526. This states that the two distributions are the same.

Students characterised by a stronger academic performance in their first semester, as measured by the GPA, get a smaller improvement in the financial test scores (although the statistical significance is limited). The same effect holds true for another measure of academic ability, i.e., student's admission test scores. This finding, i.e., a negative correlation between academic ability and financial education effectiveness, confirms that students who have an educational advantage do not benefit the most from the programme, which instead is better suited to lower-ability students. However, skills matter: students from schools with a scientific focus obtain a positive and statistically significant increase in the test score after completing the programme. This result shows that robust knowledge of basic mathematical notions (more likely among students with a STEM background than among their counterparts with a schooling background in humanities or social sciences) is a prerequisite for benefiting from a financial education programme.

The main focus of the study concerns the causal effect of treatment, i.e., being assigned to an online vs on-campus educational programme. The findings clearly indicate that there is no statistically significant difference between students assigned to the different treatments. The coefficients indicate that the gains in test scores are lower for students attending the online course, but this negative effect is not statistically significant. The possibility that the lack of a statistically significant difference may partly depend on the limited number of observations cannot completely rule out. However, the result is robust enough and suggests that the benefit from attending a short education programme on basic financial concepts does not apparently depend on the teaching method (online vs on-campus).

To investigate the effects related with the presence of non-compliant students, a model is run to keep account of the potential endogeneity of the treatment effect. The Instrumental Variables (IV) approach allows to check for this, where the effect of the treatment (online course) is instrumented through the students' assignment to this group (see Section 3.4). The main results from the second stage (i.e., where the treatment is instrumented) are illustrated in column (d) of Table 4. It is observed that the main results are confirmed, suggesting that there is a negative but not statistically significant effect associated with attending the financial education programme online, instead of the on-campus version. Thus, the result shows that there is no statistically significant effect associated with attending the programme either way is robust, and it is not driven by a potential endogeneity bias induced by non-compliant students.

4.3. Extensions: heterogeneity of causal effects explored through ML techniques

The potential heterogeneity of the treatment effect is also explored. Heterogeneity is investigated through a Machine Learning algorithm (Regression Trees, RT) where all 15 variables included in the baseline analyses are inserted as potential factors associated with the output (in particular, with the increase between pre- and post-test scores). As described in the methodology section, instead of estimating the "average" effect of the variables on the outcome (as in regression methods), this approach can be used to carry out a nonlinear estimation of the effect of the variables for subgroups of students. This higher flexibility is possible as no functional relationship need to be assumed between the covariates and the outcome. The results of the RT are graphically illustrated in Fig. 2. Each node shows two numbers: the percentage of the sample falling into this node is recorded at the bottom; while the average result (in this case, the improvement from pre- to post-test) for the sub-population of the node is placed at the top. Each node features a dichotomous condition which, if true, leads to follow the left-

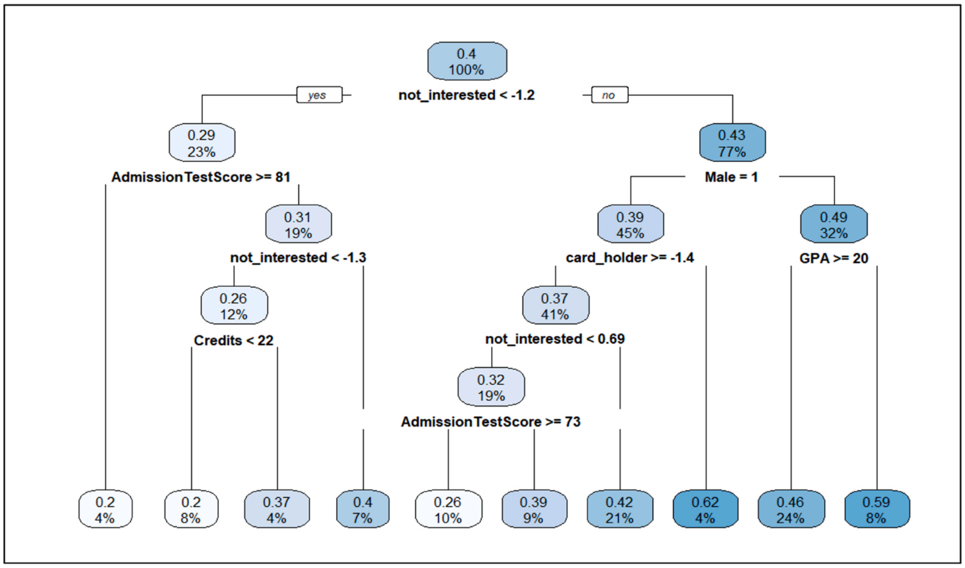

Fig. 2. The factors associated to the outcome (delta score between pre and post test): an exploration of heterogeneity using a Regression Tree. Note: for all the splits, the answer "yes" is on the left. The percentage value given in each box describes how the observations at each split are divided with reference to the variable's threshold. For the definition of the various variables, please refer to the paper, Section 3. Non-compliers are included in the analysis.

hand path, otherwise the path to take is that on the right. The leaf nodes are at the bottom of the tree.

Some interesting evidence emerges from the analysis. The first point concerns the number of variables actually used in tree construction. Only 5 variables are selected from the initial 15, namely: admission test score, credits, GPA, gender, not-interested and card-holder. Clearly, the selection of variables included in the final results depends on the adopted stopping criteria (which are, in this case, 30 observations for splitting and 0.012 as complexity parameter); however, by allowing the tree to grow, the above variables are confirmed. Among these covariates, the variable about the modality of teaching provision (online vs on-campus) does not appear in the tree constructions, and this confirms the non-statistically significant effect of the assignment to online or on-campus course.

The first variable that emerges as relevant is the interest in finance, somehow confirming the idea that curiosity in the topic is among the main drivers of the results. Following this first split, the left part of the tree contains the students particularly attracted to the topic of financial literacy (considering that the not-interested variable has been standardised, so with 0-mean and standard deviation 1), and these students represent 23 % of the sample. Comparing the leaf nodes related to this sub-population with their counterparts, it can be observed that they generally show lower improvements in their scores. As discussed above, this is probably due to the higher baseline level of the financially interested students, as also confirmed by the regression model with the pre-test as output. Moving to the right-hand side of the tree, the heterogeneity among the students' characteristics are analysed in relation with their performance in the tests. For instance, the second node level

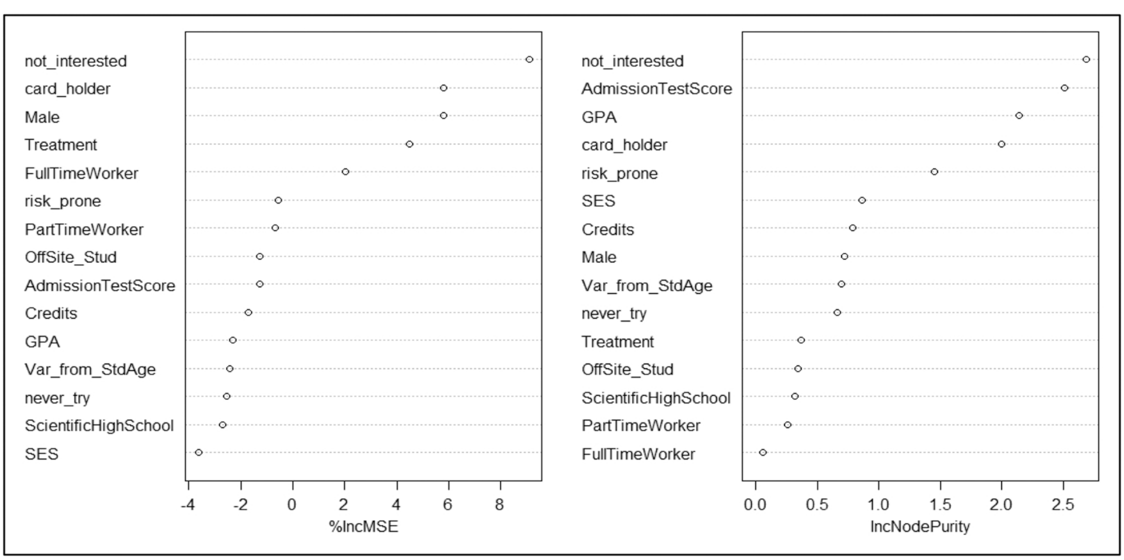

Fig. 3. The relative importance of factors associated to the outcome (delta score between pre and post test): an exploration of heterogeneity through machine learning algorithm – Random Forest. Note. Both indicators represented graphically by the Random Forest analysis show the relative importance of each variable in the model with respect to the output. In particular, %IncMSE represents the increase in squared loss if that covariate is excluded from tree sample; basically it tells how unbiased the regressor is as an estimator. IncNodePurity indicates the importance of that variable when it is included in the tree sample. Non-compliers are included in the analysis.

contains the student's gender. The information about interest in finance emerges from the female side (the right-hand side). By looking at the related leaf nodes, female students obtain the larger gains in test score. This result means that, at least in this particular context, the gender gap can be closed with little effort. It is worth noting here that the leaf node with the highest increase in scores (0.62) relates to students who are not comfortable with using payment methods other than cash (cardholder $\leq$ 1.4), corroborating the idea that financial education initiatives can be particularly effective for the less-interested students (in some sense, counterbalancing their initial lack of interest).

The last set of results from the empirical analysis is graphically reported in Fig. 3, which lists the variables that are statistically associated with the delta between the pre- and post- test scores in the strongest measure, as explored through a Random Forest technique. Both indicators represented graphically by the analysis conducted through RF show the relative importance of each variable in the model. Specifically, %IncMSE shows how much this model accuracy decreases if the variable is not considered. IncNodePurity shows the importance of each variable when it is included in the tree sample (right side of the Fig. 3). The results confirm the importance of personal beliefs and attitudes about finance; these indicators appear at the top of the ranking of the statistically significant variables and play a significant part in explaining the scoring improvement. Together with these variables, skills and academic ability also matter. As seen in the right-hand panel of Fig. 2, both GPA and admission test scores are among the most important variables. Gender enters the ranking with the same level of importance, underlining how this financial education initiative still can be differently effective for male and female students. As a further confirmation of the key findings in the present research, the variable relating to treatment (online vs on-campus) appears to be only weakly related to the scoring improvement.

5. Concluding remarks

This paper reports the results of a natural experiment conducted to test the effectiveness of an online vs an on-campus financial education programme, targeting bachelor students in an Italian leading public university. The specific design of the experiment verifies whether online education can lead to better results then traditional classroom lectures. The three-hour course/lecture deals with very basic concepts of financial literacy, such as interest rates, bonds and investment.

The paper presents three important findings. First, the financial education programme is deemed to be effective: all the students improved in their post-test results (i.e., after the programme), making substantial gains – on average, 4.0 out of a scale of [0;10]. Although not causal evidence is available about this specific finding, it appears to be credible and evident. Second, there is no statistically significant difference between attending the programme in a lecture room or online and this indicates a causal effect estimation. Third, when exploring the potential heterogeneity of the differences between teaching modes, the programme's effectiveness is associated with gender, use of payment methods and interest in finance. Specifically, the students who benefit most from the programme are those initially less interested in financial topics, especially females or males less familiar with payment methods other than cash.

Several managerial implications can be derived from these findings, which vary according to the perspective of the interested observer.

School and university managers can take advantage from the current findings to design similar interventions related to financial education at school and university level. Indeed, a clear lesson is that there is still a significant need for effective financial educational programmes, as confirmed by the students' low pre-test scores. For course lecturers and designers, the current findings suggest that such short programmes could be delivered either online or in-person, without loss of effectiveness in student achievement. Indeed, it appears that online learning can be an effective substitute to on-campus classes, at least when some specific features are met, such as those featuring in this experiment: easy technical content, intensive treatment, and a clear incentive to study and perform well in tests. Finally, these results support policy-makers in extending these types of interventions to a larger population, given that training a financially educated population is nowadays a primary objective, and given that this kind of online financial education programme would be easily scalable as a tool to spread and promote the discipline at national/international level.

The present study has some limitations related to the external validity of the study. In fact, despite the sample is assigned at random to either the online or the on-campus class, the overall sample represents a quite specific population (i.e., students attending a leading university and therefore they are highly self-motivated and committed to succeed). Moreover, the students involved in the experiment are studying for a degree in Mathematical Engineering, so their baseline knowledge of key technical and mathematical tools (which helps in financial literacy) is probably much higher than average. It follows that a similar experiment should be developed to test the effectiveness of the programme in different contexts, involving other universities and/or students in other fields. Also, the limited number of participants may affect the statistical power of these results (which, anyway, appear robust to a number of specifications). A possible extension of the study may require the involvement a larger sample of students, in order to confirm the findings of the research on a wider population. Therefore, the experiment has high internal validity and can be important to design similar experiments in different contexts learning from this experience.

Declarations of interest

None.

Acknowledgments

We are grateful to Prof. Anna Maria Paganoni, Dean of the course in Mathematical Engineering, for her advice and for agreeing to the experiment. A previous version of this paper was presented at the 2020 AEFP Conference – we are grateful to all participants for their useful comments. All the eventual errors are our solely responsibility.

Authors' Statement

In compliance with the Journal's rules, authors declare that

- R-codes are freely available upon request.
- We confirm that this manuscript has not been published elsewhere and is not under consideration by any other journal. All authors have read and approved the manuscript and agree with the submission and the revision to *Evaluation and Program Planning.*
- The data adopted have been previously anonymized following GDPR rules and the authors could not identify any of the participants to this study.
- Authors do not have any conflicts of interest, nor any financial interest.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.evalprogplan.2023.102273.

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