The effects of online financial education on student achievement: evidence from a randomized trial

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Abstract. Financial literacy is a key competence that people must owe for living appropriately in modern complex societies. A growing number of financial education programs are developed ed implemented in schools and colleges, with the aim of raising awareness and knowledge of financial competences and concepts. Therefore, robust evidence about the effectiveness of these programs is still limited. In this paper, we illustrate the results of an experiment conducted at Politecnico di Milano in 2018/19, where an innovative financial education short course has been realized and evaluated. This program made use of an innovative approach based on online learning. Its effectiveness has been assessed by comparing the effects with a traditional in-presence lecture, within a rigorous experimental setting. The findings clearly indicate that the program was effective: one week after the course, the students improved their test of a score around 4 (out of 10). In addition, there is not statistically significant difference in gains between students assigned to the online vs in-presence mode of learning. Overall, the results are very important from a managerial and policy point of view, suggesting that online learning can be a good substitute of in-presence class, where certain requirements are met (high-quality materials, limited focus of content and timing of course, low levels of initial knowledge). Policy implications are based on the opportunity of scaling the use of online learning for some, specific areas of the academic program – also paving the way to new and innovative uses of technologies for supporting online education.

Keywords. Financial education, experimental evaluation, financial literacy, online learning in Higher Education
JEL Codes. G53, I21

1. Introduction, motivation and research question

Financial literacy is currently considered to be one of the key competences that individuals must owe for living in modern societies and economies (Remund, 2010). Several factors are influencing the necessity of acquiring financial abilities during the lifetime: the increasingly complex rules of financial markets, the diminishing role of welfare services provided by the public, longer life expectancy (Lusardi & Mitchell, 2014). In such context, individuals are called to make informed decisions about a number of issues and problems that require, for instance, to understand how to save capitals for the future, to invest money in a productive way, to protect own financial data, and so forth. The positive effects of financial literacy at aggregated level (i.e. economic and social returns, see Capuano & Ramsay, 2011) call governments and institutions into action, to ensure that adequate levels of financial competences are acquired across the population (Hastings et al., 2013).

As for all types of skills and competencies, financial literacy can be improved by means of educational interventions. At the same time, international evidence is available about the scarce attention of schools and Higher Education institutions (HEIs) in including financial education in the educational programs (OECD, 2005). The situation is changing rapidly in many areas, because several national and international agencies and governments are stimulating a specific effort in increasing the levels of financial literacy, especially among the youths. For instance, the European Commission started in 2012 to promote financial education, especially for young pupils, giving the main guidelines to promote e set financial education programs, also considering the differences among European countries. Lastly, in occasion of the 2013 Russia's G20, OECD promotes a publication inviting G20 countries to advance a national strategy for financial education. As a response to these stimuli, in many countries the governments have promoted "national strategies" for developing financial education interventions, which aim at targeting the financial literacy of various segments of the population.

The Italian case is of particular interest. On one side, the international benchmarking exercises realized by OECD demonstrates that Italian students (15 years old, tested in the Programme for International Student Assessment, PISA) have very low scores in financial literacy tests, when compared with other developed countries. In fact, as pointed out by PISA 2012 and 2015 country reports, Italian 15-years-old are lagging behind their contemporary from developed countries (OECD 2013; 2016). Anyway, at the same time, the Ministry of Education launched a coordinated initiative for developing financial education in 2009 (agreement with banks, institutions and consumer associations), and since then a new attention to the topic has been actively demonstrated by the schools. Moreover, a new inter-institutional action has been taken in 2015, with the participation of the Bank of Italy, several Ministries (Economy, Education, Social Policies, etc.) and Authorities: they all together created the so-called Committee for Programming and Coordinating Financial Education. The objective of this Committee is to monitor and coordinate the various initiatives of financial education realized by single schools, institutions and organizations.

Investing in financial education is a worthwhile policy only to the extent to which the effectiveness of the specific interventions is demonstrated. Therefore, effectiveness should be

assessed on the basis of educational success in raising the knowledge of targeted topics and contents of financial literacy, as well as in influencing actual economic behaviors in real circumstances. Thus, each specific action and initiative should be ideally evaluated by means of robust statistical and econometric techniques, for establishing the causal nexus between the educational activities and gains in the acquisition of specific knowledge and skills. While the number of educational interventions is quite relevant nowadays (see a synthesis in Walstad et al., 2017), convincing evidence about their effectiveness is much weaker. Some recent reports call for more effort in producing assessments that can shed some light about the real effects of formative actions specifically devoted to financial literacy.

This paper describes a specific educational initiative realized in a major top-ranked university in Italy and assesses it causal effect on student achievement. A specific feature of this activity is that it uses online learning for transmitting knowledge of basic financial concepts. Actually, the main aim of the experiment reported in this research is to assess whether an effective financial education lecture can be conducted with the same effects online or in traditional in-presence mode. The target of the initiative is a cohort of freshmen enrolled to a course of Business Economics in the first year of the major in "Mathematical Engineering". Specifically, students were taught a 3-hours module on basic financial concepts, related with bank accounts, simple/compound interest rate, differences between shares and bonds, loans and mortgages. While half of the students attended the class in person, the other half were exposed to an online lecture equivalent to the content taught in the class. The results highlight that both groups of students experienced an increase in their knowledge of financial concepts, and that there are not statistically differences between the two groups on improvement of knowledge. This latter finding is encouraging and suggests using online learning for developing low-cost, effective, short interventions on financial education.

The present paper contributes to the current academic debate in two innovative ways. This is the first experimental evidence of the effectiveness of a financial education intervention in an Italian university. In general, the experimental evidence on the impact of financial literacy initiatives is limited, and in any case much more concentrated in the context of primary and secondary education. No previous experiments have been conducted in Italian higher education, anyway (while an experimental study about schools is presented in Becchetti, Caiazza & Coviello, 2013). In addition, this research explores the relative effectiveness of two different models of delivery of the same content (online vs face-to-face class), underlining the importance of critically defining the design of specific interventions. In this perspective, this paper contributes to the (still limited) stream of the empirical literature that analyses the impact of employing online education on student achievement, basing the assessment on rigorous experimental protocols.

The remainder of the paper is organized as follows. The next section (§2) synthetically review the state-of-the-art of the literature that deals with the effectiveness of existing financial education initiatives. The section §3 describes the experiment conducted, and the empirical analyses conducted to test the effectiveness of the educational program. The section §4 reports the main results and discusses them critically. The section §5 concludes, deriving policy and managerial implications.

2. Received literature

This section about the review of the literature deals with two main streams: the experimental evidence on the effectiveness of financial education, and the study of the impact of online education (vs. the traditional "in-person" educational mode). In the light of the existing contributions, described in the following paragraphs, we can argue that this paper contributes to the existing literature in two main ways. First, this is one of the few examples of experimental assessment of a financial education's program in Higher Education. Second, the study provides a direct evaluation of the effectiveness of two alternative ways of educational provision of the program, namely face-to-face vs online.

2.1 Effects of financial education programs

As observed by Fernandes *et al.,* (2014), the interventions about financial education inside school programs require consistent investment both for the time needed and the costs for training teachers and developing materials. Hence, along with the increasing awareness about financial education, academics have started to implement experimental interventions to understand their effects, especially for programs developed at schools and universities.

In fact, many researchers argue that providing financial education at schools and universities is the right moment as it will lead to the development of foundational knowledge and skills of young people improving their capabilities for the rest of their life (Collins *et al.*, 2015).

The purpose of this section is to give a short overview of some studies where the effectiveness of financial education programs has been tested through adequate econometric methods. We concentrate our attention on the most recent studies – from 2010 onward. The aim is to provide an overview of the methodologies adopted and the experimental designs, so that we can discuss the experimental setting deployed in our study. The characteristics shaping a specific financial education program concern with courses' features, such as when and where they are delivered, the number of students, the length and covered topics of the course, if it is mandatory or voluntary-based, if it requires teachers' training activities and if the parents are involved into financial education activities or lectures. As far as experimental features are concerned, the studies must show how participants are assigned to control or treatment groups, the specific research goal, the methods through which data are collected and the methodology employed for the empirical analysis. Overall, the results from these experiments reveal that the initiatives were generally successful for the improvement of financial knowledge of students and, in some cases, of parents. The examples mentioned are interesting from a methodological perspective, because financial education initiatives represent a new field of research and there are no standards for their evaluation. The five experiences mentioned in this section reveal some common patterns. First, students' motivation to actively join financial education programs have to be considered. In this vein, interventions must be inserted into ordinary educational activities, so that pupils are motivated – if not interested in the subject – at least in getting a good grade. Second, the interventions were designed as mandatory. Indeed, a voluntary-based participation would affect the effectiveness of the evaluation, attracting participants who self-select themselves due to their interest or weaknesses in financial literacy. Third, an adequate

randomization needs to be assured in advance for testing the effectiveness of financial education programs, allowing for causal estimates of the effects.

It must be noted that in recent years most of the experiments has been conducted in schools, while no convincing experiments have been reported for uses in HEIs – a relevant gap, that we try to fill with our research. In fact, it is worth to consider that there are examples of studies which conduct interesting modules of financial education for students enrolled in colleges (Gross, K. *et al.* 2005, Borden, L. M. *et al.* 2007, Peng, T. M. *et al.* 2007, Cude, B. J. *et al.* 2013, Xiao, J. J. *et al.* 2014), but they are not realized by means of randomized controlled trials. For this reason, we instead review some papers which employ rigorous strategies based on appropriate experiments in primary and secondary schools and only one in a university.

A first interesting example of financial education intervention comes from Wisconsin, United Stated, in Eau Claire elementary school. Batty et al. (2015) involved 4th and 5th grades pupils coming from two schools, for the participation of a five weeks' program, held by their own teachers and integrated in normal lectures. Each lecture lasts approximately 45 minutes and cover topics about basic financial literacy, particularly focused on savings and money management. This course required an active participation of both teachers and parents. Teachers were involved because they enrolled in a three-hours training course about financial topics to be enough prepared to teach in classroom, while parents were asked to fill a survey about their family and their child, such as family's income or educational level. Even if a class was (randomly) allocated to control group, it had the possibility to realize the financial education program in the second term, after the end of the experiment. The findings report significant improvements in financial knowledge, suggesting that the topic needs to be integrated into normal school activities to be effective. Another second example took place in Brazil, involving approximately 25.000 pupils from high school (Bruhn et al. 2016). The intervention reached almost 900 schools and lasted 17 months, through an integrated program into normal school curricula, requiring in-class lecture and take-home exercises. The topics covered through the program concerned basic finance and economics, thanks to a deep use of real cases connected to students' daily life. The randomness was almost assured because the request for participation to the program was voluntary-based, then researchers assigned schools to treatment or control groups according to a stratified and matched randomization. Among the most interesting aspect of this evaluation-based experiment is the strong involvement of parents, not only for collecting information about family and children, but also to raise awareness about financial education, inviting them at joining workshops at schools. Generally speaking, this program was successful on many dimensions, showing significant improvements in financial outcomes of students. However, the evidence about financial behaviors is mixed: it was observed improvements in savings, budgeting and even spillover effects on parent financial knowledge and behavior, but authors also found a significantly higher use of expensive financial products such as credit cards and installment plans and some evidence of late repayments.

A recent experiment to test the effectiveness of financial education intervention comes from Spain, through a program that involved around 3.000 students of the 9th and 10th grade from 78 high schools (Bover et al., 2018). The program started in 2014-15 with a 10 hours course, integrated into normal school curricula, so the participation was mandatory for students. The course covered basic financial topics, such as savings and interests, risk and budget, bank

accounts' typology, pension fund and insurance investments. Teachers had the possibility to organize the materials and topics as they preferred, and in some cases, they divided the topics among different subjects. Randomization has been conducted within schools. In the tests, students have been subjected also to tasks related with intertemporal choices after having studied basic concepts with the aim of understanding how attitudes (consumption vs saving) changed after financial education exposure. This allows authors to measure effects on financial behaviors, rather than only on knowledge. The evaluation showed that financial knowledge became more equal in public schools after the course, coupled with a larger increase in knowledge among at-risk students, those more at risk of dropout or who had been already repeating the class. When considering the results about financial behaviors, the analysis did not suggest that financial education improve students' intertemporal decision-making, since students made more present-oriented choices rather than long-term ones. This interesting result leaves space for further experimentations to deeply investigate the relation between knowledge and behaviors.

Becchetti *et al.* (2013) set an evaluation of a financial education intervention in high schools in Rome and Milan, in Italy. more than 900 students from 36 classes were involved from academic and vocational high schools (*Licei*, technical schools and professional schools). The course about financial and economic basics lasted three months for a total of 16 hours hosted in normal classes, so the course is considered as mandatory for students. Teachers were provided with standardized materials, that could be used to support teaching and to be distributed to students. In the randomized controlled trial, classes were assigned to treatment or control group randomly and both were asked to fill a survey before and after the course. The findings suggested that a short course of basic financial education significantly affected learning process of subgroups of students (e.g. females, academically poor performers, students without intention to enroll at university), showing a greater level of progress in terms of financial literacy within those categories which have *ex ante* poor notions of personal finance.

In a case study from Sinagapore, Barua *et al.* (2017) exploited a normal one-semester course in college about money and asset management to test its effectiveness over saving behaviors of the students. This is the only systematic evaluation of a financial education program conducted in universities/colleges and published in an academic journal in recent years. In the specific case of this college, the enrolment process for students was pretty complicated, so a rule has been set to accept or refuse in excess students: only the most motivated ones were eligible to attend it, while the others willing to join the course but refused were assigned to control group. As a consequence, this is not a perfect randomization, and must be considered as a quasi-experiment. Researchers collected data from a baseline survey before starting the course and from a post-test about financial knowledge and behavior at the end. Then information was analyzed through a difference-in-differences approach that takes into consideration the starting point of knowledge of students before the treatment (financial education course). Findings showed that the courses produced improvements in student's financial knowledge (+ 11% in scores) and in financial planning (+16%).

In summary, this section gives an overview of the main experimental approach and their main findings. Even if generally speaking the effects obtained from these interventions can be considered satisfying, a key point that should be remembered is how difficult it is to draw general conclusions about the effectiveness of one study or program. For this reason, it is worth

producing more robust evidence on a larger number of interventions and financial education activities – an objective that we pursue in the present work.

2.2 The effectiveness of online educational programs

In addition to the aspects described in the section §2.1 about the effects of financial education programs, the present research adds an important component, which is testing the effectiveness of alternative form of content provision, namely in-presence vs online. In recent years, there is a growing literature which assesses whether online educational provision is able to obtain the same achievement gains as traditional, face-to-face activities – especially in Higher Education. In this section, we report some findings obtained by previous research conducted through an appropriate experimental design.

The first robust experimental evidence on the effect of online education on student achievement is offered by Figlio *et al.* (2013). In a class of "Principles of Microeconomics" of a USA public college, students were randomly assigned to a live (in-presence) or an online-only delivery mode. No statistically significant difference was observed on student achievement when the overall sample of nearly 300 students was considered. Though, the effect was heterogeneous by ethnicity, gender and ability level, as online delivery resulted to be detrimental for Hispanic, male and low-ability students to the extent of a 3.5 to 11.3% score decrease with respect to the traditional class. Bowen et al. (2014) expanded the randomization to six USA campuses and found no statistically significant difference between the in-presence and the blended format, where the online delivery was mixed with a one weekly hour of face-to-face lecture. Across the 600 students attending the statistics courses object of the study, the difference between the two delivery modes was not significant neither in terms of success rates nor in terms of student achievement, regardless any personal characteristics that could have induced any heterogeneity of the effects. Joyce et al. (2015) further contributed by randomizing 725 students into a traditional or a "compressed" class of introductory microeconomics in a public USA college, where a weekly lecture substituted the standard twice-a-week format. The same online materials were made available to both classes. A sort of substitution effect was visible in the compressed class, where students watched videos more frequently than in the traditional format. The effect on student achievement was mixed, given that the grades of the students in the traditional format were 0.21 standard deviations higher than those in the compressed format in the mid-term exam, though this difference was not significant in the final grade. Alpert et al. (2016) compared three delivery modes by randomly assigning students to a traditional, a blended or an online-only class of economics principles in a USA college. Results showed that students attending online performed 5 to 10 points lower than those in the traditional format, while the blended delivery did not report any significant difference. When investigating the heterogeneity of the effects, low-ability students resulted to perform poorer when assigned to the blended or to the online format, meaning that blended educational can still be detrimental for specific subgroups of students.

Whilst the mentioned examples all come from the context of USA, recently Cacault *et al.* (2019) provided empirical evidence on the take-up and the effect of live video streaming in the

University of Geneve (Switzerland). In the experiment, first year bachelor students were randomly offered access to a live video streaming platform for eight of their compulsory courses. The randomization occurred also in the accessibility of the streaming across weekly lectures, so that around 23,000 combinations of student-course-week observations were collected over two terms. Results showed that the take-up level was relatively low, as only 10% of the students used the streaming service when available, and only when random shocks (like bad weather conditions) made the cost of attendance particularly high. By triangulating economic theory and results, authors showed that the counterfactual to streaming as well as the effect on achievement differed by level of ability. For high-ability students, the proper counterfactual was no-attendance and the effect of streaming the lectures was positive to the extent of a 2.5% increase in the exam grade. For low-ability students, class attendance was the most convenient counterfactual and the negative effect amounted to a 2% decrease in the exam grade.

Summarizing, some robust experimental evidence is available for the use on online education in HEIs. Such evidence shows a null or negative effect of 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 favor of the latter. The heterogeneity of the effects within the sample is usually relevant; specifically, the lack of in-person interaction is particularly detrimental for low-ability students, who instead benefit the most from class attendance.

3. Methodological approach: the experimental design

3.1 A description of the experimental setting

The experiment of this research is set in major top-ranked Italian university, specialized in Engineering, Architecture and Design. In particular, the chance for the experiment comes from the development of a MOOC by the Mathematics Department about financial basics for university students. This MOOC is uploaded within the university portal dedicated to web lectures. The website gives professors the possibility to record online lectures about different topics, providing to Bachelor or Master students the possibility to become acquainted on a topic, to revise the preparation for an exam, to strengthen their soft skills before entering the job scene. The MOOC subscription is possible for university through the use of students' personal code assigned by the Institution at the moment of enrolment, in this way the content creator has the possibility to track the activity of a student. In the experiment analyzed in this paper, the online course is the one about financial basics, its content is organized through seven weeks, each one contains several videos on the topic addressed in the week. Once watched the entire week, students have the possibility to test what they have learned by performing a short test.

In our experiment, we considered a sample of first-year students enrolled in a degree course of Mathematical Engineering in the University. Specifically, the first-year mandatory course of Business Economics, which was offered in the Spring 2019 has been exploited to deliver the

finance course and its evaluation. Along with normal course scheduling, a lecture about basic financial contents is introduced. Given the high number of students enrolled in the degree course, the Institution decides to divide students into two classes based on their last name: A-L in the first class and M-Z in the second one – hence the class assignment is completely random. Such feature enabled to conduct a randomized field experiment to test whether the effectiveness of the financial education training is affected by the method of delivery, as one class is assigned to the face-to-face-only and the other to the online-only teaching method. The high degree of comparability between the two classes is due to the fact that the same professor who held the online course also taught the face-to-face class. The scheduled lesson lasts about three hours for the live class, or the equivalent workload delivered through online fruition, that is a combination of videoclips for a total of 55 minutes. The total number of students is 403, divided into two classes of 226 and 177 students, respectively. The first class is assigned to the online-treatment group, attending a MOOC-based lecture, while the second one attends the face-to-face lecture during normal scheduling of Business Economics course.

The structure of the experiment is divided into three steps: pre-test, training and post-test. Pre-test aims at capturing the financial literacy level of participants, together with assessing their baseline attitudes in term of financial trust, spending habits or interest/competency in financial topics (Annex 1 reports the questionnaire). Students filled the survey at the beginning of a lecture of Business Economics. Then, the live-only class attended the lecture about basic financial topics held in class by the professor from Mathematics Department of the university, while the other class attended a lecture of Business Economics. The online-only class was required to enroll and to attend the MOOC course about basic finance, in particular the module dedicated to bank account and interest rate, bonds and stocks, investments and mortgage. Exactly, the content of these videos was taught in live-only class. The third step is the post-test, one week after the pre-test, where students were asked to fill a test about the topics taught in the lectures/videos. In this case too, students filled the test during a Business Economics lecture.

Some details of the course are worth of some clarification. Business Economics lessons must not be mandatorily attended by students (there is not a systematic check for the presence of students in the single lessons), but the attendance is strictly suggested by the University, so the presence is normally pretty high, with an average of 180-200 students per class (around 80% of enrolled students). Students were not aware to be part of an experiment, so their only motivation to actively participate to both tests was given by the possibility to add one-point on the exam's final grade. Indeed, students correctly answering to 50% or more of the questions in the post-test get one extra point in the Business Economics final grade (over a 30-points scale). Lastly, the pre and post tests are identical for both classes, so the comparability is assured. Checking participation to the online platform, we were able to assess whether students assigned to the online treatment actually attended the lectures. We were also able to detect whether students assigned to the face-to-face class actually also accessed to the online platform. Hence there can be two possible types of non-complying students: those who should have watched the MOOC but they did not, and those assigned to live-only class who also enrolled the MOOC, so receiving a kind of double treatment.

Together with test scores and attitudes towards finance, collected directly through the surveys filled during the experiment, additional relevant information has been obtained from the administrative office of the University. Data has been supplied and treated in a completely anonymized way. The administrative data included in the analyses deals with (i) career information such as score at the entrance test, GPA (i.e. the average grades obtained in the single courses, weighted by the number of formative credits of each course), credits obtained before attending the course, attempted exams before the course and (ii) personal information such as gender, citizenship, socio-economic status (SES) and high school track completed. As described in the subsequent section §3.3, we report details and descriptive statistics about these variables in the Table 1.

3.2 The content of the financial education program

The MOOC "*Finanza per tutti*" (the Italian for "Finance for all") is a MOOC, provided in Italian language, it was built in 2017. It is freely available at a dedicated online platform of the University. The course aims at teaching basic concepts of financial literacy to citizens, starting from daily problems, as for example, how to get a mortgage, how to invest savings, how to choose a bank account. The course is divided into three main blocks. The first block relies on bank accounts, simple/compound interest rate, differences between shares and bonds, as well as loans and mortgages. The second block is devoted to financial risks, insurance and behavioral finance, highlighting the main errors done by investors. Finally, the third block deals with advanced financial products, like options and swaps, as well as some hints on the legislation that protects the investor. Each block consists of several videos, which length is approximately 8 minutes; all of them are built as a discussion between an animated character (with a problem to be solved) and a professor.

For the experiment described in this paper, seven videos of the first block has been selected, the content of the videos was the following:

- The flow of time and interest rates: simple vs compound interest;
- Interest rate and time horizon: dealing with annual, semi-annual, quarterly interest rates;
- Bonds and ratings;
- The market interest rate curves;
- The relationship between bonds prices and the market interest rate curves;
- Loans: IRR, APR, and nominal interest rate;
- Mortgages/loans payment calculation: how to compute rates in a fixed interest rate framework.

The total time to watch all videos is approximately 55 minutes, that can be considered equivalent to a face-to-face class of approximately three hours.

To be completed

3.3 Data

The total number of students who attended both the pre and post-tests was 365: 158 in the face-to-face class and 207 in the online-only class, with a retention rate higher than 90%. We need to consider non-compliant students. Hence, in addition to the online-only (n=181) and the live-only (n=114) groups, we labelled (i) no treatment (n=17) the students assigned to the online class, who did not attend the MOOC, and (ii) double treatment (n=28) the students assigned to the face-to-face class who also attended the MOOC.

In addition to the results of tests about financial literacy, demographic and performance information is considered in the analysis. In the first class we consider information on age, gender, if he or she comes from another city or not, if he/she has a part- or full-time job, student's high school typology and their socioeconomic status. This latter information is derived from the allocation of student to a fee scale, based on their families' income. The fee scale is from 0 (fee exemption) to 10 (maximum contribution). For each student we also have performance data, as his/her GPA reported on a scale from 18 (the minimum grade to pass an exam) to 30, the total amount of credits (CFU) obtained in the first semester (all students are freshmen), the admission test score (on a scale 0-100) and the no-show exam rate, so the percentage of student's absenteeism per exam (this indicator measures how many times the student resulted as "absent" the day of the exam, and is another proxy for academic readiness). The baseline descriptive statistics are reported in the Table 1.

Insert [Table 1] around here

Data reveal that there are no structural differences between students in the treatment and control group (online vs face-to-face). In both groups, students who are not in the median age of the cohort are around 3.5%, male students are around 60% and the average index of socio-economic scale is 6 (out of 10). About 40% of students are off-site, 16% work part time and less than 1% instead work full-time – it is important to recall here that there can well be a higher proportion of full-time working students, but they would not be present in class during the experiment. When looking at the performance in the first semester, students obtained on average between 19 and 20 formative credits (out of a maximum of 30 available). The admission test score is around 74 (out of 100) in both groups of students, and a proportion higher than 80% attended a scientific high school. The no-show exam rate is between 5% and 8%. The only dimension under which the two groups of students look statistically different is the average GPA obtained in the first semester, which is 20.6 for the students assigned to the online course and 22.8 for the students assigned to the group of face-to-face class. Anyway, the picture that emerges from the analysis of these statistics is that the randomization, realized through the last name of students, worked in an appropriate way and students assigned to the two groups (online vs face-to-face) actually have the same relevant characteristics, on average.

On the basis of the answers provided by students in the questionnaire, about their beliefs and attitudes, we classify them in three archetypes through a Principal Component Analysis. We select the first three components of the model, which explain more than 50% of the total

variance and for which the *eigenvalue* is greater than 1. To better interpret the different components, we look at the component loadings. The model identifies three groups (architypes), and the corresponding coefficients for the various dimensions investigated are reported in the Table 2. The first group of students has been labeled "not interested", as the most important components are: the negative interest in financial topics (-0.552), the agreement with the idea that financial topics will never be interesting for them (0.564) but, at the same time, the ability to cope with financial concepts, once informed (0.557). The second group is that of "risk-averse" students, for which risks associated with financial investments are judged as unmanageable (-0.649) and the absolute necessity of acquiring a lot of information before making financial decisions (0.682). The third archetype of students is that of "card-holders", and the most important loadings are the holding of a bank account (0.488) and a credit card (0.529), as well as the use of the credit card itself (0.489) – they can be considered as financially-active students. As explained later in more detail, for each student we standardize the values of the three components for each student, and we insert these values into the econometric models as explanatory variables with the goal of capturing students' current financial attitudes and behaviors.

Insert [Table 2] around here

3.4 Econometric and statistical specification

The empirical analysis is conducted by mixing two main methodological approaches. The baseline results, which illustrate the average effect of the treatment (the online course and the face-to-face lecture) are derived through an OLS regression on experimental data. These baseline results are supplemented by a model that uses Instrumental Variables for testing their robustness. In addition to the baseline estimates, Machine Learning (ML) algorithms are employed to search for potential heterogeneity of the treatment's effect. As expressed by Schiltz et al. (2108), the methodologies of the ML family are particularly well suited for identifying relationships between influencing factors and the outcome of interest (in our case, the test score in the financial literacy) are highly nonlinear and interacted with students' characteristics. Specifically, Regression Trees (RT) and Random Forests (RF) are implemented to study the heterogeneous effects of the financial education initiative on different subpopulations of students.

With reference to the first set of methodologies, we firstly estimate an OLS regression on the pre-test scores, in order to be informed about the covariates that predict students' initial performance. The model can be expressed as follows:

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

where, for each *ith* student, the dependent variable y_{PRE_i} is regressed against a set of student level covariates X_{1_i} related to individual characteristics, academic ability and relative attitudes in finance. This latter dimension is made of the component scores resulting from the PCA described in Section 3.3. Finally, we control for the randomized assignment to the treatment

$TREAT_i$, a dummy variable equal to 1 when the student is assigned to the online delivery mode and 0 otherwise, which is expected to be non-significant in this regression, given the randomization.

The second model is designed to capture the treatment effect by means of the following OLS regression:

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

where the response variable accounts for the difference between the post and the pre-test, both measured on a 100-points scale, while student level covariates (X_{1_i}) are the same mentioned in model (1). The variable of interested is here represented by $TREAT_i$ which indicates the assignment to the treatment (=1) or to the control group (=0). Given the existence of a small group of non-compliers, as described in Section 3.3, we control for their presence by means of the dummy variables $NOTREAT_i$ and $DOUBLETREAT_i$. The first variable identifies student in the no treatment group, while the second refers to those in the double treatment group. In addition to this, we estimate a third model in which we consider compliers only. In this specification, the intention to treat (ITT) effect is equivalent to the average treatment on the treated (ATT) effect, given that the model is run on the subpopulation of students complying with the assignment to the treatment.

Finally, given that the presence of non-compliers may imply selection issues, we estimate the treatment effect by means of a two-stage-least-square (2SLS) Instrumental Variable (IV) approach. The instrument must be a variable related to the treatment but unrelated to the outcome, in order to identify the treatment effect. In this case, the random assignment to the treatment or control group represents a good instrument being at random by definition, and hence is used to estimate the first stage regression as follows:

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

where the output variable p_i represents the probability of compliance with the treatment assignment. Then, the second stage regression can be estimated as:

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

where the final output variable $\Delta_{POST-PRE_i}$ is estimated against the vector of student level covariates and the fitted values of p_i.

Along with traditional econometric models, we adopt a more Statistical (Machine) Learning approach, through the use of decision trees. This choice is made to deeply understand the relationships among variables, always considering the results in tests as variable of interest. To this regard, Regression tree is adopted: the basic idea is to release linearity constraints, through the implementation of a non-parametric statistical procedure. The main output we obtain with decision trees is the identification of mutually exclusive subgroups of a population whose members share common characteristics that influence the dependent variable, so in our case the difference in scores obtained between pre- and post-tests.

In general, decision trees' algorithms begin with one "node" or group, that contains all the sample and it is called "parent node". The procedure then examines all possible independent variables and selects the one that results in binary groups that most differ with respect to the dependent variable. This choice is made following a predetermined splitting criterion. The parent node is then splitted into two descendent nodes according to the independent variable that is selected. Again, within these two nodes, the tree-growing methodology continues by assessing each of the remaining independent variables to then choose the best ones for the splitting. When the process stops, so the tree is pruned, we will look at the so-called "leafs", that contain the subgroups we are interested in. The dependent variable of decision trees can be continuous or categorical, in our case, since the Delta in PostPre tests scores is a continuous variable, the adopted method is the Regression Tree. In this case, the leaf will show the average improvement in score (the *Delta*) among the students belonging to that node (Lemon, S. *et al.* 2003).

From a more formal standpoint, suppose that all the observations are spread in space, the idea behind Regression Trees is to divide the space into high-dimensional rectangles, creating homogeneous subgroups that minimize the RSS (Residual Sum of Squares), the splitting criteria for this method. In order to perform the recursive binary splitting, we first select the regressor X_j and the cutpoint *s* such that splitting the space into regions $\{X|X_j < s\}$ and $\{X|X_j \geq s\}$ leads to the greatest possible reduction in RSS. (The notation $\{X|X_j < s\}$ means the region of space in which X_j takes on a value less than s). That is, we consider all regressors $X_1, \ldots, X_p$, and all possible values of the cutpoint s for each predictor, and then choose the predictor and cutpoint such that the resulting tree has the lowest RSS. In greater detail, for any j and s, we define the pair of half-planes $R_1(j, s) = \{X|X_j < s\}$ and $R_2(j, s) = \{X|X_j \geq s\}$, and we seek the value of j and s that minimize the equation:

$$\sum_{j=1}^{J} \sum_{i \in R_j} (y_i - \hat{y}_{R_j})^2 \quad (5)$$

where $\hat{y}_{R_j}$ is the mean response for the training observations in $R_1(j, s)$, and $\hat{y}_{R_2}$ is the mean response for the training observations in $R_2(j, s)$. Finding the values of j and s that minimize can be done quite quickly, especially when the number of features p is not too large. We then keep going the process, looking for the best regressor and best cutpoint for the splitting, always minimizing the RSS in the resulting regions, until the stopping criteria is reached. Among the main stopping criteria there is a limitation in the number of observations contained in the leafs, in our case we set it as 30 (James *et al.* 2013).

The random forest is an ensemble predictor based on multiple regression trees, first proposed by Breiman in 2001. The purpose of Breiman derived from different methodologies, among which there is "bagging" (Breiman, 1996). The main feature of bagging is the growing of an ensemble of trees and letting them vote for the most popular class (Breiman, 2001), so the ones most chosen when splitting a node. Basically, Random Forest takes an ensemble of individual decision trees and, for each one, it considers only a subset of predictors as split candidates (Schiltz, F. *et al.* 2017). The main difference is that with the previous mentioned methodologies at each split all the predictors are considered, this can result in having always the same "strong" predictors as relevant. Hence, with Random Forest, though the consideration of only a subset

of variables at each split, we can obtain more differentiate trees that will be averaged. The result will show the ranking of the most voted classes in regression trees (Shi, T. *et al.* 2006). In this case, the trees used in RF are regression trees, so the splitting criterion is defined with Mean of Squared Error (MSE).

In this study, Random Forests analysis is performed using the R package called randomForest, which can be used for both classification and regression. For each variable, this function returns the increase in mean square error (%IncMSE), that estimate the variable importance. In fact, it estimates the percentage increase in MSE of the model when that variable is out of bag, and then average this over all trees (James, *et al.* 2017). While IncNode Purity expresses the model of tree nodes' influence: it expresses a measure of the total decrease in node impurity that results from splits over that variable, averaged over all trees (James, *et al.* 2017)

4. Results from the empirical analysis

Before assessing the effect of attending the financial education program online instead of assisting a vis-à-vis lecture, we focus on the determinants of scores obtained by the students in the pre-test, i.e., before the education program was implemented. The results are reported in column (a) of Table 3. First, we certify that there are no differences between students who then have been assigned to different treatments, something that could otherwise invalidate the possibility of assessing the treatment's effect on the post-test scores. Two features of a student are associated with different scores in the pre-test. Male students report higher test scores than female students, corroborating a gender bias that characterizes the financial literacy of young people in Italy, and in various countries (see Fonseca et al., 2012). Also, students who work full-time are on average more financially literate than non-workers, most likely because they needed to deal with financial issues for their professional activities. In any case, it is important to recall here that these students represent less than 1% of the overall sample. When considering students' attitudes and beliefs, not surprisingly the pre-test scores are lower in case of students who are labeled as "not interested" (group 1), and higher in case of students defined as "financially active" (group 5). Academic ability matters for financial literacy measured before the educational intervention: both Admission test scores and GPA in the first semester are positively associated with higher pre-test scores.

Insert [Table 3] around here

The main findings of this research are reported in the columns (b) and (c) of Table 3. Preliminarily, it is important to recall that the dependent variable is the increase in test scores between pre and post treatment – in other words, we do not analyze the determinants of financial literacy scores at the end of the program, but instead we focus on the factors associated with growth of test scores before and after the implementation of the training program. Models 2 (column b) and 3 (column c) differ because the former includes controls for the presence of non-compliant students, while the latter excludes them from the empirical analysis. The findings are however robust and do not change between the two models, the results look qualitatively and quantitatively very similar.

The two main features of students, associated with an increase in financial literacy, are gender and being employed full-time. Male students and full-time workers experience negative gains in test scores when compared with female students and non-workers. It is interesting to note that the two groups of students are those who reported higher scores in pre-test. Accordingly, an interpretation of the negative association of these features with test scores' increase is that such students are already skilled in the financial field, and they do not benefit from the proposed training program. It can also be the case that such students, underestimating the complexity of some basic financial concepts, did not put enough effort to study new contents which instead became part of the tests. In the same vein, it is also interesting to observe that students with a high value of principal component belonging to the groups of "cardholders" (group 3) benefit in a more limited way from the training program, again probably because they already have a good level of initial knowledge – all else equal, these students gain less than similar students who are less interested or risk adverse. Students who were deemed as "not interested" (group 1), on the contrary, have experienced a statistically significant and positive benefit from attending the financial education program. These results corroborate the idea that financial education programs (at least, those targeting basic concepts) can have a stronger effect on a subpopulation of students who possess lower initial knowledge, and risk not to produce benefits for already skilled people.

Students who revealed a stronger academic curriculum in the first semester, as measured by GPA, obtained negative gains in financial test scores (although the statistical significance of this effect is somehow small). The same relationship holds with reference to another measure of academic ability, namely the test score obtained in the admission process. This finding – i.e. negative correlation between academic ability and financial education effectiveness – seems to confirm that students who have an educational advantage do not benefit from the program, which then seems better suited for low-ability students. In any case, skills matter: indeed, students with a scientific high school background obtained a positive and statistically significant increase in test scores thanks to the training program. This result indicates that robust knowledge of basic mathematical skills (held by these students more than their counterparts who attended a high school in humanities or social science field) is a prerequisite for benefiting from a financial education program.

The main focus of the study is about the causal effect of treatment, i.e. being assigned to an online vs face-to-face educational program. The findings clearly indicate no statistically significant difference among students assigned to different treatments. Actually, the coefficients indicate that students attending the online course obtained a lower gain in test scores, but such a negative effect is not statistically significant. We cannot rule out completely the eventuality that the lack of statistically significant effect could be partly due to the number of observations. However, the result is robust enough and suggests that attending a short education program about basic financial concepts does not different statistically depending on the provision method (online vs in presence).

As indicated in the section §3 about methodology, we also tested a model in which we kept into account the potential endogeneity of the treatment effect, which in our experimental design can stem from the presence of non-compliant students. To check for this effect, we implement

an Instrumental Variables (IV) approach, in which the treatment's effect is instrumented through the assignment to treatment. The main results coming from the second stage (i.e. where the treatment is instrumented) are illustrated in column (d) of Table 3. We observe that the main results remain unchanged suggesting that there is a negative but not statistically significant effect of attending the financial education program online instead than face-to-face. Thus, we can conclude that the result showing that there is no statistically significant effect of attending the program in either way is robust, and not driven by potential endogeneity bias induced by non-compliant students.

We also explore the potential heterogeneity of the treatment effect. As detailed in the section §3.4, the exploration of heterogeneity has been conducted through performing a machine learning algorithm named Regression Tree (RT), in which all the 15 variables included in the baseline analyses are inserted as potential factors associated with the output (also in this case, the increase between pre- and post-test scores). As described in the section about the methodology, this approach allows to depart from estimating "average" effect of the variables on the outcome (typical of the regression methods), but instead models the various potential subgroups of students for which the variables are potentially associated with the outcome in a non-linear way (especially, without assuming any functional relationship between the covariates and the outcome). The results of the RT are graphically illustrated in Figure 1. Before going deeper in investigating the main insights coming from the decision tree, a short explanation about how to read it is needed. Hence, each node shows two numbers: at the bottom there is the percentage of the sample falling in this node; while at the top the average results (in our case, the improvement done from pre- to post-test) obtained by that (sub-)population. Lastly, when reading the tree, each node shows a condition: if it is true, the path to follow is on the left, otherwise on the right. At the bottom of the tree we can find the so-called "leafs". Now some interesting patterns emerging from this supplemental investigation can be deepened. The first information comes from the number of variables actually used in tree construction: in fact, among the starting 15, only 5 of them are effectively adopted: admission test score, credits, GPA, gender, not-interested and card-holder. Clearly, this number depends on the stopping criterion we adopted, however if letting the tree to grow the variables used were always these. Among these covariates, the effect of treatment does not appear in tree construction: this confirms the non-significant effect of the assignment.

First, the primary variable that emerges as relevant for splitting the sample is the interest in finance, somehow confirming the idea that the curiosity over the topic is the main driver in this model, too. Following this first split, we find in the left part of the tree those students particularly attracted by the topic (considering that the not-interested variable has mean =0 and standard deviation =1), who represent the 23% of the sample. If comparing the leafs related to this sub-population with their counterpart, is evident that generally they show lower improvements in scores. This is probably due to the higher baseline level of financial interested students, as also confirmed by the regression model with pre-test as output. Moving to the right part of the tree, it represents more heterogeneity among students' characteristics related to performance in tests. For instance, the second level of nodes is occupied by student's gender. The interesting information arrives from the female part (the right one): generally, by looking

at the related leafs, females reached major improvements than males. This can mean that, in this particular context, with little effort the gender gap can be leveled. It is worth noting here that the leaf node with the highest increase in scores (e.g. 0.62) is represented by males that are not confident with payment instruments alternative to cash (card-holder < -1.4), corroborating the idea that such interventions of financial education can be particularly effective for less-interested students (in some sense, counterbalancing their baseline lack of interest).

Insert [Figure 1] around here

The last set of results from the empirical analysis comes from the evidence reported in Figure 2, which indicates the list of variables that are more importantly statistically associated with the outcome of interest (i.e. Δ Post-pre test score), as explored by mean of a random forest (RF; see also the section §3.4 for statistical details). Both indicators represented by the analysis conducted through Random Forest show the relative importance of each variable in the model. Specifically, %IncMSE represents the increase in squared loss if excluding that covariate from tree's sample, basically it tells how much the regressor is an unbiased estimator (left side of the Figure). Instead, IncNodePurity reports the importance of each variable when it is included in the tree's sample. The results point a confirming once more the relevance of personal beliefs and attitudes about finance; these indicators appear at the top of the ranking of statistically significant variables and have a strong magnitude in explaining the outcome of interest. Together with these variables, skills and academic ability matter: as seen in the right panel of the Figure 2, both GPA and score in admission test appear among the most important variables. At the same level of importance, gender enters the ranking, underlining how this financial education intervention still can be differently effective for male and female students. As a further confirmation of the key finding for the present research, the variable about treatment (online vs in-presence class) appear as one of the least important covariates associated with the outcome.

Insert [Figure 2] around here

5. Discussion, policy and managerial implications, concluding remarks

To be completed)

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Table 1. Descriptive statistics of students' characteristics and results

Panel A. Descriptive statistics

Variables	Treatment group (Assigned to online)	Control group (Assigned to f2f)	t-test (p-value)
Individual characteristics			
Deviation from standard age	0.035 (0.234)	0.035 (0.402)	0.997
SES (Index of socioeconomic 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 in the paper, and to Panel B of this table

Table 1. Descriptive statistics of students' characteristics and results

Panel B. Variables' definition

Variable	Description
Individual characteristics	
Deviation from standard age	Difference b/w expected student's age (e.g. 19 or 20 y.o.) and actual one.
SES (Index of socioeconomic 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
Individual attitudes and beliefs about finance	
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

Table 2. Principal Component Analysis on the variables about financial attitudes at students-level, and clustering of the students' archetypes

Variable	Component 1: 'not interested'	Component 2: 'risk-adverse'	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 imply assuming 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 operations	-0.04	-0.021	-0.133
It is better not to trust financial market participants	-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 issues	**0.564**	-0.025	0.017
Once you get informed, you can deal with financial issues	**0.557**	-0.019	0.017

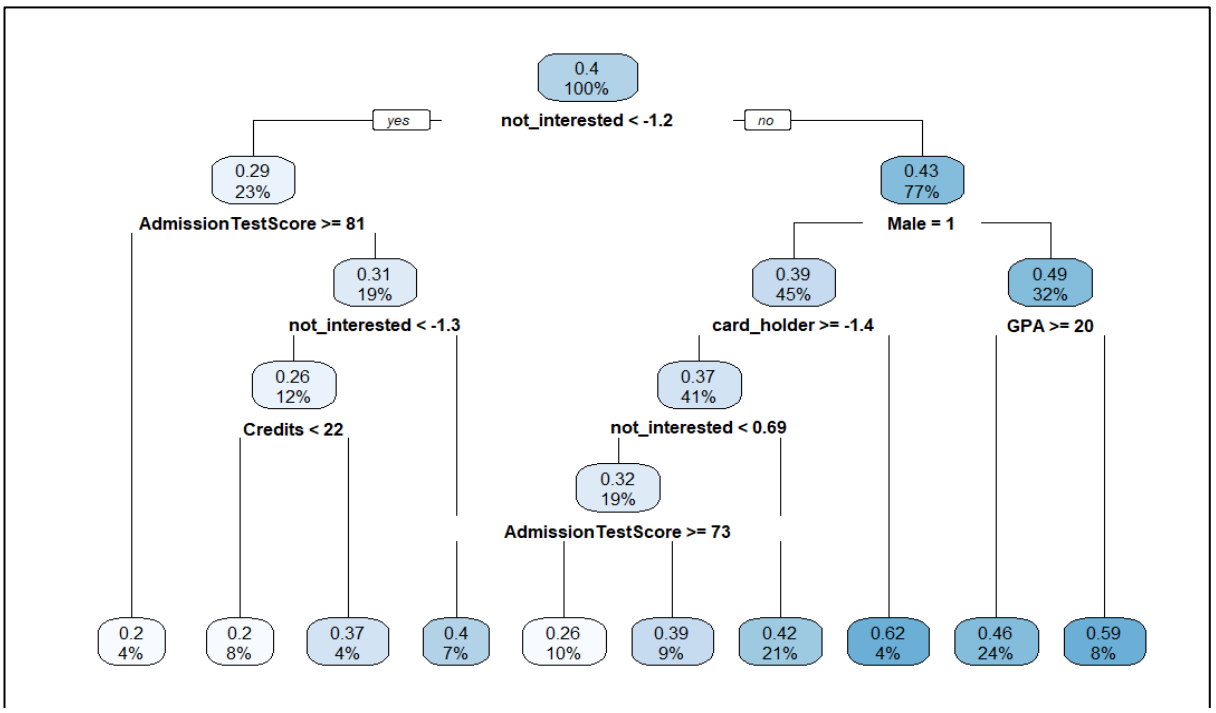
Notes. Component loadings reported. Values in bold refer to the variables most representative for each component, being the highest values in absolute terms. The results are obtained by means of a Principal Component Analysis.

Table 3. Results from the econometric analysis – the effects of the educational program on students' scores in financial literacy test

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

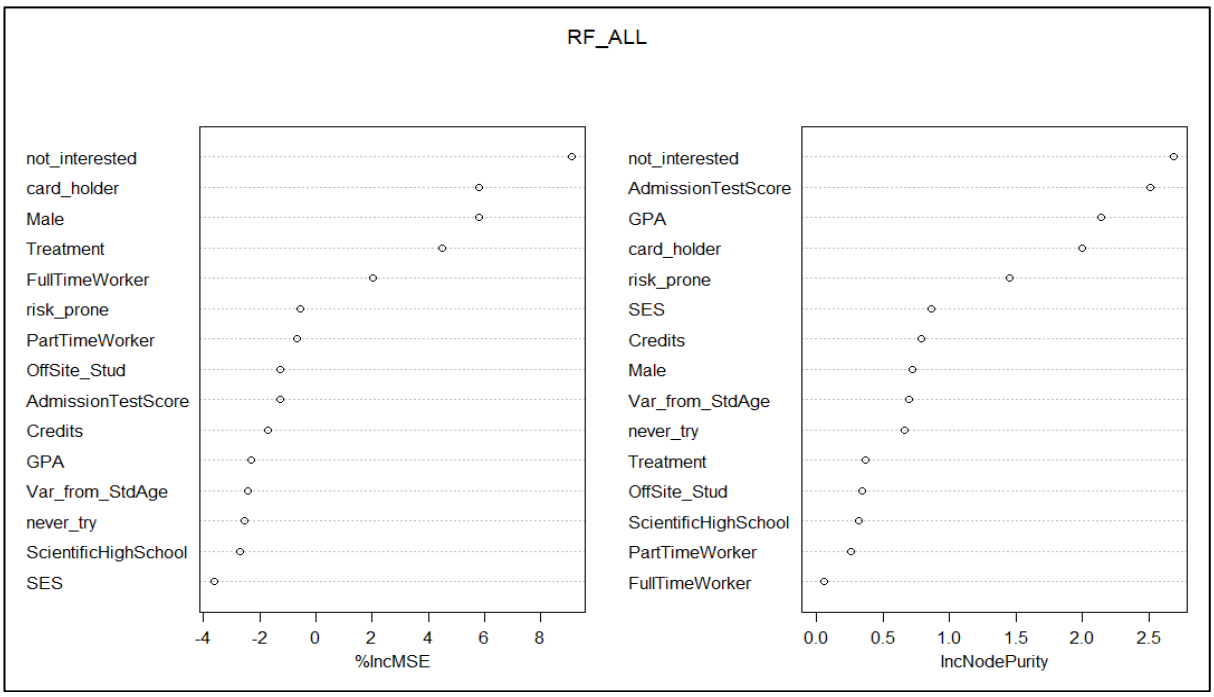
Notes. Standard errors in italic, small font. *** p<0.01, ** p<0.05, * p<0.1
The dependent variable in Models 1, 2 and 3 is calculated as the difference between (i) post test scores and (ii) pre test scores - standardized on the basis of the number of questions.
For the definition of the various variables, please refer to the paper, section §3.
The number of non-compliers is =45 (that is, 13% of the sample)

Figure 1. The factors associated to the outcome (ΔPost-Pre score): an exploration of heterogeneity by means of machine learning algorithm – Regression Tree



Note: for all the splits, the answer "yes" is on the left. The proportion reported in each box describes how the observations at each split are divided according 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.

Figure 2. The relative importance of factors associated to the outcome (ΔPost-Pre score): an exploration of heterogeneity by means of machine learning algorithm – Random forest



Note. Both indicators represented by Random Forest analysis show the relative importance of each variable in the model to respect to the output. In particular the %IncMSE represents the increase in squared loss if excluding that covariate from tree's sample, basically it tells how much the regressor is an unbiased estimator. While IncNodePurity stands for the importance of that variable when it is included in the tree's sample. Non-compliers are included in the analysis.