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Abstract

In this paper we investigate the effects of using a Facebook page exclusively devoted to a first year Mathematics course in a large Italian public university. Posts and discussions supported traditional face-to-face lectures and students could freely post queries and get help from professors and peers. We use a newly constructed dataset to measure how this influences the grade they achieved and the probability of getting a passing grade.

Firstly, we find that active students, who read and post more often, perform slightly better than non active ones, who mainly read the content, but the effect is not significant. However, other measures of activity, such as the frequency of visualization of the page significantly increase the probability of earning a passing grade, after controlling for students' characteristics and robust ex-post measures of ability.

Secondly, we exploit a quasi-natural experiment to compare the performance of students having access to Facebook with that of a large sample of similar students who were not offered the support page in another branch of the university. Difference-in-difference estimates show that students who could access online discussions gain on average 1 additional point out of 30. The effect is, hence, significant but rather small and of possibly limited practical relevance.

Keywords

Facebook, virtual discussions, academic performance, quasi-natural experiment, difference-in-difference

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The Effects of Facebook Discussions on Academic Performance¹

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Abstract

In this paper we investigate the effects of using a Facebook page exclusively devoted to a first year Mathematics course in a large Italian public university. Posts and discussions supported traditional face-to-face lectures and students could freely post queries and get help from professors and peers. We use a newly constructed dataset to measure how this influences the grade they achieved and the probability of getting a passing grade.

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1 Introduction

In the last decade online platforms, digital tools and interactive material are increasingly being used to support traditional teaching methods, Xu and Jaggars (2013). Online learning, in some form, will surely be an increasingly important component of university education, Joyce et al. (2014). This raises the issue of analysing in detail the effect of these new tools on students' satisfaction and academic performance.

Sharing the common idea of using technology and web based applications to support traditional teaching methods, several different tools have been developed and are rapidly spreading in higher education. For example, MOOCs (Massive Open Online courses) are courses entirely taught online, with open access and a potentially unlimited number of participants, see Haber (2014). They were first introduced in 2008 and, although low completion rates are typically an issue, they have become a popular mode of instruction since 2012. Students typically learn by watching recorded lectures, reading material and working on weekly assignments. Blended learning is another form of technology driven tool developed to support education. Although there is no consensus on a unique definition of it, blended learning encompasses several forms of hybrid teaching methods characterized by a combination of both face-to-face learning and online based activities, Bonk and Graham (2012). Flipped learning is a form of blended learning in which students typically use videos prepared by the instructor to study on their own the topics and then discuss and solve exercises in class with colleagues and the instructor, while in traditional lectures the opposite usually occurs.

In this paper, we assess an experiment that consisted in using a Facebook page to support traditional face-to-face lectures of a standard first year Mathematics course for students in Economics at a large Italian public university. Our contribution is to quantify the effects of activity on the page on students' performance, measured in terms of the grade achieved on the math exam and the probability of passing the exam. We do so by controlling for various student characteristics including demographic variables and several measures of ability, such as grade point average and number of credits achieved along the academic career.

Moreover, we take advantage of the fact that Mathematics is a compulsory course in the university where the experiment took place and the same course is taught in a different town to otherwise identical cohorts. We compare the performance of students

who could access the Facebook page with the one of similar students of parallel courses who were not offered a specific support page. In particular, our key methodological contribution is to use a difference-in-difference approach to compare students' math grades in the two samples.

One of the characteristic feature of our experiment is that we choose to use the social network Facebook to host academic discussions, securing a high participation that may not be reached using other tools. For a comprehensive review of the use of Facebook by students and teachers see Hew (2011).

A large body of literature has recently developed trying to quantify the effect of alternative teaching methods on students' performance; but only few studies are conducted in a rigorous manner, using quasi-experimental designs or controlling for student characteristics, Means et al. (2009). There is no clear answer on which method is able to produce better learning outcomes, with different studies arriving to opposite conclusions. Two early examples are Navarro and Shoemaker (2000) and Brown and Liedholm (2002); the first presents evidence that students taking an introductory macroeconomics online course have significantly better test scores than students taking the same course in a live lecture format; the second reports the opposite result for students taking an introductory microeconomics class.

There are several papers investigating the effects of video lectures, as opposed to live ones, on students. Figlio et al. (2013) is an insightful work comparing classes where undergraduate students are randomly assigned to attend either live or internet-broadcast lectures. They find no significant difference in the two groups with male and lower-achieving students performing significantly better in live classes. Xu and Jaggars (2013) is another example where the authors estimate the impact of online versus face-to-face lectures on students' performance, using an instrumental variable approach. Their analysis yields robust negative estimates for online learning: attending a particular course in an online format rather than face-to-face would decrease students' likelihood of completing the course and lower their final mark.

Differently from these examples, our Facebook page is more similar to a blended learning experiment as the page is conceived as a tool to support face-to-face lectures, and not to substitute them; in this respect our paper is similar to Bowen et al. (2014), Joyce et al. (2014) and Kwak et al. (2014).

Bowen et al. (2014) examines the performance of students in an introductory statis-

tics class held on six public university campuses. The authors compare the performance of students attending a traditional class with the performance of students whose class material is delivered online supplemented by one weekly class meeting. The study reports no overall difference in performance, measured by their exam grade. Joyce et al. (2014) is a similar recent study that compares the performance of students who met once per week in a hybrid format, with the one of students in a traditional lecture format of the same class, who met twice per week. The authors show that on average students in the hybrid format scored around 2.5 percentage points less than students in the traditional format, a modest effect according to the authors. Our paper is also related to Kwak et al. (2014) as the authors use a difference-in-difference approach to evaluate the impact of blended learning on students' performance.

As far as the general use of Facebook is concerned, both positive and negative effects on student performance have been documented, with the majority of them tending to be negative. Kirschner and Karpinski (2010), for example, find that an increased activity on Facebook is correlated with significantly lower grade point average and reduced students' time dedicated to studying. The authors claim that multitasking may play a negative role when students switch from academic activities to other online actions. Pasek et al. (2009) criticize the previous results and, using three different datasets, find no significantly negative effect of Facebook use on students' grades, controlling for student characteristics such as ethnicity and socio-economic status; on the contrary in one of the three dataset they find a weak positive effect.

The previous two papers study the effect of Facebook on academic performance, when it is used for general purposes of leisure and networking, but not specifically related to academic activity. The key contribution of our paper is instead to investigate the effect of activity on the social network, when it is specifically used as a support to traditional face-to-face lectures. Two qualitative examples of the effect of Facebook, when it is used as a supporting teaching tool, are Bosch (2009) and Kabilan et al. (2010). The first, presents results of an experimental use of Facebook at the University of Cape Town, and it draws positive conclusions on the use of Facebook as an additional learning channel. The second, uses Facebook as a supporting tool for an English language course, and it also draws positive conclusions. Over 60% of surveyed students agree or strongly agree on all positive evaluations of Facebook regarding improvements in language writing and reading skills, motivations and confidence.

The rest of the paper is organized as follows. Section 2 describes the course and the page and section 3 the data. Sections 4, 5 and 6 present methods and results for the econometric models used; section 7 concludes.

2 The course and the page

The course “Mathematics” is a compulsory first-year course for undergraduate students enrolled in one of the Economics degrees offered by the university. Instructors are tenured faculty members who typically have taught the course for many years. Topics covered included calculus, functions of one and two variables, some linear algebra and elementary notions of financial discounting. Lectures are held 3 times per week and last 90 minutes, for a total of 30 meetings. In the two years examined in this paper, classes were crowded and more than 150 students attended the lectures. Students could choose to take the exam in two ways: they could either sit two midterms in November and December splitting in half the material covered, or one unique final held in two occasions in January. The course took place in the first semester, between mid September and mid December.

At the beginning of the course a Facebook page was activated and administered by the instructors, with a twofold aim. First, it offered a quick and effective way to provide organizational and administrative information on practical aspects of the course such as the timetable of lectures and availability of office hours. Secondly, the page provided an additional tool for students who could ask both their colleagues and the instructor questions on difficult topics, additional explanations on the teaching material and help to solve exercises. In fact, mathematics is perceived as a difficult subject by Economics students, coming from different backgrounds and with different quantitative skills. Moreover, the page allowed shy students, who would not dear to ask questions in a crowded class, to post their doubts and get quick feedback. On a weekly basis, the syllabus was updated and posted on the page, together with additional exercises and mock exams allowing students to check their proficiency on required basic tasks.

3 The data

We use a newly constructed dataset by merging information from two different sources: a survey filled out by students at the end of the course, before any exam, and administrative data retrieved from the University’s official records.

The Facebook page was activated for the first time in the fall semester of 2011 and the same experiment was repeated the following year. Both years, an online administrated survey was filled out by students on a voluntary basis. The two courses were identical in terms of syllabus, provided material and instructors; we compared survey answers and students’ observable characteristics in the two waves and found no meaningful difference.² Therefore, we pool data from the two waves and overall we have a sample of 355 undergraduate students, 217 and 138 from 2011 and 2012, respectively.

In the 2011 survey providing personal information (name or student ID) was voluntary, while this information was required the following year, under the standard agreement that only aggregate data would have been disclosed. The knowledge of the identity of the respondent is necessary to match the answers from the survey with administrative data and retrieve students’ characteristics and academic records. In the econometric analysis we focus on the restricted sample of $N = 236$ students who provided identification and were successfully matched with the administrative data (102 and 134 are drawn from the samples of 2011 and 2012, respectively). The overall sample is homogeneous with respect to the subject studied (Economics), status (undergraduate) and ethnicity (Caucasian, with a handful of exceptions).

3.1 Survey data

Information collected with the survey includes sex, level of activity on the online platform, perceived usefulness of the page and information on the amount of time spent on the Facebook page and studying for the exam. The survey was screened by a statistician to eliminate possible biases in the way the questions were worded. Table 1 reports some of the most relevant questions asked in the survey and the frequency of chosen

²The only statistically significant difference is that in 2012 visualizations of the Facebook page were more frequent, with less students visualizing the page few times a week and more several times per day.

options.

Table 1: Selected survey questions and answers, $N = 236$.

Question	Options	Percent
Which kind of user are you?	fairly active (read and post few times)	30.9
	not very active (mainly read)	66.1
	one of the least active	1.7
	one of the most active	1.3
How often did you visualize the page?	when notifications appeared	0.8
	before the exam	3.0
	few times a week	23.3
	once a day	46.6
	several times a day	26.3
Do you think the page was useful? (1-10)	useful 1	0.4
	useful 6	0.8
	useful 7	5.9
	useful 8	16.9
	useful 9	25.0
	useful 10	51.0
Evaluate the usefulness in terms of final grade out of 30: which is the added value?	no difference	3.8
	1 point	15.3
	2 points	33.9
	more than 2 points	38.1
	don't know	8.9

Two thirds of the students defined themselves as “not very active” and approximately one third as “fairly active”, only 3 and 4 students picked “one of the most active” and “one of the least active”, respectively. In the econometric analysis we merged them with the other two factors “fairly active” and “not very active”. Visualizations were frequent: 26 percent of students visualized the page several times per day, 47 percent once per day and 23 percent few times a week. Students highly appreciated

the experiment as 51 percent valued the usefulness of the page at the top level and 25 and 16.9 percent of students choose 9 and 8 respectively. Students expected gains from the page to be significant and more than two thirds of students thought they would gain 2 points (33.9 percent) or more (38.1 percent).³

3.2 Administrative data

The second source of information is data retrieved from the University’s official records, after obtaining written permission from ADiSS (Area Didattica e Servizi agli Studenti), the Teaching and Students’ Services Division, which allowed the retrieval of selected information and prescribed strict anonymization of personal information. This data includes demographic information such as sex and province of residence; information on the students’ educational experience prior to entering university such as type of high school attended and final mark; and university records such as track (“corso di laurea”) chosen, year of enrolment, exams passed, grades and credits achieved. This data is both matched with the survey data and used as a source to build the control group in the quasi-experimental approach.

We consider several indicators of students’ performance, used in the econometric analysis to control for student “quality” and proxy unobserved ability. Since mathematics is a first year course, at the time of the experiment on-track students had passed few exams and collected few credits, preventing us from having adequate and robust measures of their ability. Therefore, we waited and tracked their performance up to July 2014 and computed their grade point average and number of credits, obtaining robust *ex-post* measures of student ability.

Grade point average is a synthetic measure of students’ performance; in our sample the median is 23.8 (mean 24.1) and 19 and 29 are the minimum and maximum.

The number of credits achieved per year, compared to grade point average, gives additional information on students’ speed, see Brugiavini et al. (2014).⁴ In the Italian system students are not required to sit the exams at the end of the course, and some students happen to procrastinate taking exams. In the mathematics course there were

³In Italy, the grade is routinely expressed in thirtieths: failing to reach 18/30 forces the student to retake the exam. We further assume that 32 is equivalent to the top grade 30/30 *cum laude*.

⁴In the Italian system each exam is worth a certain amount of credits, depending on the work load required, and students need to earn 180 credits to obtain the undergraduate degree.

both on-track students, enrolled in the first year, and out-of-track students, enrolled in the previous years, who decided to attend the course after some time. To take this into account, we standardize the total number of credits gained and obtain a measure that is comparable across different enrolment years.⁵ The median number of standardized credits, ranging from 0 to 1 by construction, is 0.54. The correlation between this measure and grade point average is 0.5. This means that there are “fast” students with relatively low GPA and “slow” students with relatively high GPA.

We consider two additional performance measures: the high school grade and the score obtained in a formal mathematics entry test that first-year students take upon enrolment. The high school grade is achieved at the end of a 5-year schooling period required by law to access university. It is a general and noisy measure of scholastic skills, as it is a summary of the performance in several distinct disciplines. In our sample, the median high school grade is 79.65, on a scale from 60 to 100. Regarding the entry test, failing to achieve a given threshold temporarily halts the admission process, until the student gains additional credits by attending special-purpose refresher courses in mathematics and proves his/her proficiency. In our sample the median is 20, on a range from 7 to 36. Compared to the high school grade, the entry test score is a more specific measure of the quantitative and mathematical abilities of the student. However, due to administrative reasons, data on the entry test is only available for the 2011 wave.

The grade achieved in the mathematics exam is the dependent variable used in the econometric analysis. The median grade is 24 and 18 and 30 *cum laude* are the minimum and maximum. We consider relevant in our study only the grades of students who successfully passed the exam in the midterms or in the two examinations held in January, after the students followed the course. We make the assumption that, if the access to online discussions had an effect, it is only for students who actively followed the course and took the exam right after. We believe it is extremely unlikely that students who took the exam in June or later could still benefit of conversations or material posted months heretofore. In the sample 176 out of 236 students (75 percent) succeeded in passing the exam within the January sessions.

⁵For every year of enrolment we rank students according to the total number of credits they achieved and compute the percentiles of each distribution; we assign to each student the corresponding percentile. For each year, the student with the least (most) credits will get 0 (1). A value of, for example 0.3, means the student performed better than 30 percent of the students enrolled in the same year, in terms of number of credits achieved.

3.3 External validity

Students decided to fill in the survey on a voluntary basis. This may cause a self-selection problem and therefore our sample may not be representative of the broader population of potential students. If those who appreciated the Facebook page or have strong quantitative skills are more willing to respond to the survey, and these students respond differently to online activity on the Facebook page, then our results cannot be generalized to typical students enrolled in a large introductory math course. The ideal situation would have been to have all students attending the course fill in the survey (and provide their student ID), but this could clearly not be enforced.

As magisterially exemplified in Figlio et al. (2013), we did our best to check whether the students who volunteered to fill in the survey and provided ID are different in observable ways from the entire population of students enrolled in the same Economics degree since 2009. We compare students' performance in terms of: grade point average, number of standardized credits achieved and high school final mark. Table 2 summarizes the comparison between the two samples and column 3 is the p -value of a Kolmogorov-Smirnov test, where the null hypothesis is that the two samples were drawn from the same distribution.

Table 2: Comparison between averages of students in the sample and enrolled from 2009 to 2014 (1141 subjects) in the same Economics degree. The third column provides the p -value of Kolmogorov-Smirnov test.

	$\bar{x}_{sample}$	$\bar{x}_{pop}$	p -value
GPA	24.08	24.22	0.94
credits std	0.54	0.56	0.22
high school	79.65	77.8	0.14

As can be seen from the table, for the three variables grade point average, standardized number of credits and high school final mark, we cannot reject the null hypothesis. The results of a simpler t -test on the difference of the means yields similar results: p -values for GPA, standardized credits and high school final mark are 0.38, 0.42 and 0.03, respectively. Moreover, to rule out the hypothesis of time trends, we repeated the comparison between distributions using sub-samples of the population, made of students enrolled since 2010, 2011 and so on; results qualitatively and numerically do

not change.

In summary, the sample appears to be reasonably representative of the overall population of the students or, at least, we see no obvious biases although it was not randomly selected.

4 Activity and math grade

4.1 Basic empirical model

Our goal is to estimate the effect of students’ engagement on the Facebook page on the grade they achieved on the mathematics exam. To explore this issue quantitatively, we start with a linear regression model estimated by ordinary least squares (OLS). We fit a simple linear regression model of the form:

$$grade_i = \beta_0 + \beta_1 \cdot activity_i + \beta_2 \cdot ability_i + X_i' \beta_3 + \varepsilon_i \quad (1)$$

where the *grade* obtained in the mathematics exam is the dependent variable and *activity* is the main explanatory variable. Therefore, the coefficient β_1 quantifies the effect of students’ online activity on the Facebook page on their math grades. X_i' is a row vector of student characteristics and additional controls, including demographic variables and perceived usefulness of the Facebook page. In addition, we include year fixed effects since the experiment has been repeated for two years.

The most active students could earn better grades thanks to their activity on the Facebook page, which is the possible causal effect we are interested in. It could instead be that better students *ex-ante* are more likely to participate to online discussions *ex-post* thinking this would improve their performance. To take this causality issue into account, we use several measures to control for student ability such as: grade point average, standardized number of credits achieved, score obtained in the university entry test and high school final mark.

The concept of activity is multidimensional and nuanced and, therefore, its measurement is far from trivial. In the baseline case, activity is a dummy variable equal to 1 if the student defined himself as “fairly active (I read and post few times)” or “one of the most active” and it is equal to 0 if the student is “not very active (I mainly read the content)” or “one of the least active”.

Defined in this way, one could interpret the effect of activity as the marginal benefit obtained by students who not only read the posts, but also actively wrote on the Facebook page. Nevertheless, also the students who simply read the content, perhaps the less performing ones, could benefit by spending time on the page or frequently visualizing the information posted by their colleagues. Therefore, as additional measures of activity, we consider the frequency of visualizations and the time spent by students on the Facebook page.

4.2 Robustness tests

As a robustness test, we use a Tobit model to account for the fact that the dependent variable, namely the grade achieved in the mathematics exam, is limited both from below and from above by 18 and 30 *cum laude*. If there is a significant number of predicted values below and above the truncation points this may bias the results and in this case the truncated regression is a valid choice.

The OLS and Tobit specifications cannot account for another potential problem. In the previous regressions only the students who successfully achieved a passing grade, greater than or equal to 18, are included in the sample, therefore, using this non-random sample might bias our estimates. To correct for this bias, we use the Heckman selection model, see Heckman (1979), originally used to estimate the determinants of wage offers in the US labor market. In the first stage we estimate the probability of achieving a passing grade using a Probit model. As a predictor for the probability of passing the math exam, we use the variable standardized number of credits, and expect a positive and significant correlation. The estimates from the selection equation are used to predict the probability of achieving a passing grade for each individual. In the second stage we correct for the selection bias including a transformation of the predicted individual probabilities as an additional explanatory variable in a linear regression with grades as a dependent variable.

4.3 Regression results: activity and math grade

The estimates of the OLS model are shown in Table 3, together with other models used as robustness checks. The math grade is the dependent variable and activity is the main explanatory variable; it is a dummy equal to 1 if the student is “fairly active”

or “one of the most active”, 0 otherwise. We test the relevance of different subsets of regressors and subsequently eliminate the ones that are not statistically significant. The first column shows the estimates of the selected OLS model.

Table 3: Effect of activity on math grade, OLS model and robustness tests.

	<i>Dependent variable: math grade</i>			
	<i>OLS</i>	<i>robust linear</i>	<i>Tobit</i>	<i>Heckman selection</i>
	(1)	(2)	(3)	(4)
activity	0.282 (0.460)	0.381 (0.494)	0.417 (0.513)	0.404 (0.462)
GPA	1.213*** (0.105)	1.261*** (0.113)	1.356*** (0.121)	1.280*** (0.117)
entryz	0.218*** (0.060)	0.237*** (0.064)	0.267*** (0.068)	0.219*** (0.059)
entryno	4.045*** (1.363)	4.747*** (1.464)	4.977*** (1.563)	4.145*** (1.331)
useful10	0.990** (0.433)	1.133** (0.465)	1.125** (0.485)	0.965** (0.423)
Constant	−10.777*** (2.731)	−12.674*** (2.933)	−15.456*** (3.199)	−12.900*** (3.226)
Time FEs	YES	YES	YES	YES
Observations	176	176	176	236
R ²	0.513			0.516
Adjusted R ²	0.495			0.496
F Statistic	29.633***			
Wald Test			166.087***	

Note:

*p<0.1; **p<0.05; ***p<0.01

As can be seen from the table, we find weak evidence in favour of the hypothesis that active participation to discussions (i. e., reading *and writing*) helps students to improve their grade at the exam. Regression coefficients indicate that activity has the

expected sign: the ones who read and post perform better than not active ones, who mainly read the content, and earn 0.28 additional points, but the magnitude of the difference is small and neither statistically nor practically significant.

As largely expected, students with higher grade point average perform significantly better in the exam, earning 1.2 points for every additional GPA point.

The quantitative and mathematical abilities that students have when they enter university, measured by the grade on the entry test, are positively correlated with the math grade, and the estimated correlation is 0.2. Since the average grade on the entry test is 19.5, the average increase in math grades is approximately 4 points. The dummy for students who did not take the entry test has a similar magnitude. The correlation between *activity* and *GPA* is -0.04 and the correlation between *activity* and students' score in the entry test, *entryz*, is 0.02. Therefore, we believe there is no self-selection into activity driven by ability.

The dummy for students who valued 10 the usefulness of the page is positive and statistically significant: students who ranked the usefulness at the top earned on average 1 additional point, after controlling for the other covariates. Interestingly, those who found the page most useful (before taking the exam) actually benefited from it. This suggests that not all students are alike and not everyone profits from online discussions in the same way. On the Facebook page short posts and status updates are the main means of communication, information flows rapidly and, therefore, posts can rapidly sink and are no longer visible in a very short amount of time. It might be that students who use smartphones or tablets, or are often online, are able to ride the information flow and take advantage of it. Instead, students who prefer traditional tools as textbooks, paper and pen may not be able to benefit from this hectic environment and could be distracted from the option to be active online.

We include time fixed effects to take into account that in the sample we have students from the two waves 2011 and 2012 and, as expected, being in one or the other wave has no significant effect on math grades, controlling for the other covariates. The coefficient of determination, in the basic or adjusted form, tells us that the model explains approximately 50% of the variation in the data, which is a reasonable amount for a cross section. The elimination of the non significant variables increased the adjusted- R^2 and did not change the magnitude of the other significant variables. The variables we dropped from the model are: sex, dummies for perceived usefulness of

the page equal to 8 and 9, number of standardized credits achieved, expected gains and high school final mark. Moreover, the alternative activity measures, frequency of visualizations and time spent on the page (for the 2012 sample) are not significant.

As previously explained, we perform several robustness test: the estimated coefficients of a robust regression, a Tobit model and the Heckman selection model are displayed in columns 2–4 of Table 3. First, to control for heteroskedasticity, we fit a robust regression model and the estimated coefficients closely resemble those in the first column: the coefficient for activity increases to 0.38 but it is still not statistically significant. Second, we use a Tobit model to take into account that the dependent variable is bounded between 18 and 30 *cum laude*. The coefficients are quite similar to the ones obtained with OLS and the same can be said for the marginal effects (0.40, 1.31, 0.25, 4.8 and 1.08 for the independent variables). Third, we fit a Heckman selection model to take into account the possible selection bias due to the inclusion in the model only of student who achieved a passing grade. In the selection equation, the standardized number of credits achieved is a significant predictor of the probability of passing the math exam. The estimated coefficients of the outcome equation are shown in column (4) of Table 3; they closely resemble those of the other specifications suggesting that using only students who successfully achieve a passing grade does not bias the estimates. We repeated the estimation of the Heckman model with different specifications in the first stage using, for example, the grade achieved in the statistics exam as a predictor of the passing probability, since it is another compulsory quantitative course; the results both qualitatively and numerically do not change.

To sum up, our results are quite robust with respect to several specifications, the estimated parameters are similar across different models and the relations among variables look quite stable.

5 Activity and passing probability

We perform a second set of regressions to estimate the effect of students' engagement on the Facebook page on the probability of achieving a passing grade on the math exam. We use a Probit model of the form:

$$P(pass_i = 1 | activity_i, ability_i, X_i') = \Phi(\beta_0 + \beta_1 \cdot activity_i + \beta_2 \cdot ability_i + X_i' \beta_3) \quad (2)$$

where Φ is the c.d.f. of the standard normal and the dependent variable is a dummy equal to 1 if the student passed the math exam, earning 18 or more, and 0 if he failed or did not sit the exam within the two examinations held in January. As in the OLS case, we use different measures of activity, and control for student ability using several *ex-ante* and *ex-post* performance measures. Moreover, we test the robustness of our results by using alternative models for binary dependent variables.

Compared to the OLS regressions, standard errors are smaller and the estimates are more precise, reflecting the bigger sample size. As in the OLS model our baseline measure of activity, the dummy equal to 1 if the student is “fairly active” or “one of the most active” is not significant. Instead, when we use the frequency of visualizations as a measure of activity, we find interesting results: Table 4 shows the estimates of the effect of the frequency of visualization of the Facebook page.

Table 4: Probit model for the effect of visualizations on passing probability.

<i>Dependent variable: pass (1 if $grade \geq 18$)</i>		
	(1)	(2)
GPA	0.253*** (0.050)	0.151*** (0.058)
vfewtweek	0.919* (0.489)	0.913* (0.522)
vonced	1.041** (0.471)	0.993** (0.502)
vseved	1.265*** (0.490)	1.141** (0.527)
Constant	−6.357*** (1.252)	−5.259*** (1.405)
Additional controls	NO	YES
Time FEs	NO	YES
Observations	236	236
Log Likelihood	−114.775	−101.978
Akaike Inf. Crit.	239.551	225.956

Note: *p<0.1; **p<0.05; ***p<0.01

In column (1) we consider a model where the independent variables are restricted to the dummies for the number of visualizations (a few times per week, once a day and several times a day) and the grade point average to proxy for unobservable ability.

We find that the frequency of visualizations is positively and significantly correlated with the probability of passing the math exam. Moreover, visualizing the page more often monotonically increases the probability of success, compared to students who visualized the page rarely, i.e., only before the exams. Computing marginal effects, we find that visualizing the page a few times a week, once a day and several times per day increases the probability of passing the exam respectively by 23, 26 and 32 percent.

As expected, grade point average is positively and significantly correlated with the probability of success, as every additional point in students' GPA increases the chances of passing the math exam by 6 percent. In our sample the least and most performing students have a grade point average of 19 and 29 respectively, so the best students have 60 percent higher chances of passing the exam, other things being equal, compared to the least prepared ones.

In the second column of Table 4 we included several control variables, as well as time fixed effects to take into account that in the sample we have students of the two different waves. Results are robust, as the estimated coefficients are similar to those in column (1), both in terms of magnitude and significance. Visualizing the page a few times a week, once a day and several times a day increases the probability of passing the math exam by 22, 24 and 28 percent and the marginal effect of grade point average is still a sizeable 4 percent.

As a further robustness test, we used alternative models for binary dependent variables, such as the Logit and the linear probability model. Results are similar to those obtained with the Probit model and the estimates confirm the monotonically increasing relation between the frequency of visualizations and passing probability, both with and without additional covariates.

6 Quasi-experimental design

Several parallel math courses are taught at the same university and we exploit this fact to implement a quasi-experimental design to compare the performance of students who had access to online discussions with the one of similar students who did not have

access to any support page. In particular, we use a difference-in-difference approach to measure the difference in math grades between the two groups.

6.1 Difference-in-difference strategy

We call T the treated group, made of students that took the math exam in the town where the online support page was offered and C the control group made of students in parallel courses who did not have the page. We estimate the effect of active participation to online discussions on the grade achieved in the math exam by comparing the average change over time in math grades for students in the T group with the average change over time for students in the C group. We combine data from the survey and administrative data reaching a sample size of $N = 2380$ students.

The difference-in-difference requires data measured at two or more points in time; we therefore assume that the experiment took place in the 1st and 2nd examinations held in January, as previously discussed, and use the 3rd and 4th examinations as the post experimental period.

The math courses followed by the treated group are by all means similar to the parallel courses attended by the control group. All courses have the same program, textbooks, number of face-to-face lectures, exam mode and availability of office hours. In Table 5 we compare students' observable characteristics in terms of math grade, grade point average, number of standardized credits achieved and high school final mark; column (3) is the p -value of a Kolmogorov-Smirnov test.

Table 5: Comparison between the treated group T and the control group C .

	$\bar{x}_T$	$\bar{x}_C$	p-value
math grade	22.310	22.266	0.937
GPA	23.786	23.925	0.350
credits std	0.528	0.563	0.007
high school	77.847	77.269	0.306

Overall the treated and the control group are similar in observable characteristics: the only statistically significant difference is in the earned standardized credits, but the magnitude of the discrepancy is small and, if anything, it shows that the students in

the control group are slightly better *a priori*, thus reinforcing our findings.⁶ We further investigated the comparability of the samples in two ways.

First, we compared the “quality” of high schools in the two towns where the math courses were held for the treated and the control group. We used an online portal that allows to compare different types of high schools, within a given region, in terms of the performance achieved *ex-post* by high school graduates when they go to university.⁷ Grade point average, credits and an index combining the two are used to compare high schools, and weights are used to allow the comparability across different faculties. This tool should advice students on which are the high schools that better prepare students for university. Results of the simulations done do not show any major concern and, if anything, they suggest that high schools in the town where the math course was activated with the Facebook page are slightly better.

Second, we compared teaching evaluations filled in by students at the end of all courses, both in the track where the experiment took place and in the other economics degrees; the questions asked are identical. We focus on teaching evaluations of the math courses and on an average measure of all courses in the two academic years studied 2011/12 and 2012/13. On a scale ranging from 1 to 5, average satisfaction for the math course taken by treated students is 3.57 and 3.67 respectively in the 2011 and 2012 wave; in the control group it is respectively 3.31 and 3.33. The average evaluation of all courses in the treated group is 3.15 and 3.22 respectively in 2011 and 2012 and 3.18 and 3.25 for tracks in the control group.

The higher appreciation of the math course in the treated group may depend on the quality of the instructor but also on the availability of the Facebook page.

In the econometric analysis we control for student ability using the different performance measures, and include time and track (“corso di laurea”) fixed effects as students in the different tracks in the control group may have different quantitative skills or differ in unobservable ways.

The math courses of the treated and the control group have different instructors that may have (slightly) different grading methods. However, the comparison of the math

⁶Results of a *t*-test comparing means yields similar results; p-values for math grade, GPA, standardized credits and high school mark are 0.827, 0.183, 0.059 and 0.311 respectively.

⁷The website used, developed by the *Fondazione Giovanni Agnelli* is:
<http://www.eduscopio.it/percorso-studenti-scelta-scuola-superiore#mapSlide>

grades of the 1st and 2nd examinations with the ones of the 3rd and 4th examination allows us to net out this potential bias. To identify the causal effect of Facebook activity we are implicitly taking the *parallel trend assumption*. In our case, this means that if there is a difference in grades between the January session and the following ones, this difference is the same for all students, both in the treated and the control group, and that each instructor uses the same grading method in the different sessions. We believe this is a reasonable assumption.

If self-selection into the course with the Facebook page and students' ability were correlated in an unobservable way, controlling for student characteristics would not be enough to eliminate the selection bias. However, with our quasi-experimental design we can eliminate this bias as, at the time of enrolment, students did not know that just in the T group the experiment would take place and, in any case, students would not chose in which course to enrol depending on this.

After controlling for student characteristics and instructor grading methods, and including fixed effects to control for the different waves and tracks, it can be argued that the remaining difference between the T and the C group is mainly due to the availability of a discussion page and, hence, the difference-in-difference provides a estimate of the effect of student activity on the Facebook page on their performance.

Figure 1 illustrates the difference-in-difference estimate, representing the effect of online discussions.

Figure 1: Difference-in-difference estimate.

The treatment (control) group is depicted by the T (C) line. $T_{1,2}$ and $C_{1,2}$ are the average math grades in the treated and control group at t_1 , when the experiment took place, while $T_{3,4}$ and $C_{3,4}$ are average math grades at t_2 . The difference between average math grades at t_1 cannot be imputed entirely to Facebook, say because instructors of the T group may tend to give higher marks or due to other unobservables. The difference between $T_{3,4}$ and $C_{3,4}$ allows us to net out this potential bias and therefore the difference-in-difference $\hat{\beta}_D$ is a consistent estimate of the (causal) effect of Facebook activity on math grades for the treated group.

We estimate the following difference-in-difference equation:

$$grade_i = \beta_0 + \beta_1 \cdot January_i + \beta_2 \cdot T_i + \beta_D(January_i * T_i) + X_i' \beta_3 + \varepsilon_i \quad (3)$$

where $January_i$ is a dummy equal to 1 if student i passed the exam in the 1st or 2nd examination held in January and 0 if he/she passed the exam in the 3rd or 4th examinations in the following session; T_i is a dummy equal to 1 for students in the treated group and 0 in the control group and X_i' is a row vector of additional covariates. The composite variable $January_i * T_i$ is then a dummy variable indicating when $T_i = January_i = 1$, referring to students in the treated group who took the exam in January and potentially benefited from activity on the Facebook page.

6.2 Difference-in-difference estimates

Table 6 reports the coefficients of several specifications of the difference-in-difference model.

In column (1) we only include the dummies $January$, T and their interaction; due to omitted variable bias the model is not correctly estimated, and the R^2 is very low.

In the model in column (2) we add grade point average as an additional explanatory variable; this greatly improves the explanatory power of the model and changes both the magnitude and the significance of the estimated coefficients. The interaction term $January * T$ is the difference-in-difference estimate that, as previously discussed, measures the effect of activity on the Facebook page on students' math grades for the treated group. The estimated coefficient is positive and statistically significant at 10% and students who are active on the Facebook page and pass the math exam in January gain on average 0.81 supplementary points. Observe that the additional performance

of the treated students, 0.322, is statistically and practically insignificant, whereas being treated and taking the exam soon has a much larger marginal effect that can be attributed to the role of online activity.

Table 6: Difference-in-difference for the effect of Facebook activity on math grade.

	<i>Dependent variable: math grade</i>			
	(1)	(2)	(3)	(4)
January	1.546*** (0.188)	0.539*** (0.159)	0.411** (0.163)	0.284* (0.162)
T	0.902*** (0.263)	0.322 (0.219)	0.032 (0.266)	-1.941** (0.893)
January*T	0.623 (0.555)	0.814* (0.461)	1.273*** (0.482)	1.275*** (0.481)
GPA		1.058*** (0.032)	1.058*** (0.040)	1.107*** (0.040)
Constant	21.075*** (0.165)	-3.452*** (0.763)	-1.706 (3.077)	-2.976 (3.029)
Additional controls	NO	NO	YES	YES
Course FEs	NO	NO	NO	YES
Time FEs	NO	NO	NO	YES
Observations	2,380	2,380	2,349	2,349
R ²	0.034	0.334	0.353	0.383
Adjusted R ²	0.033	0.333	0.346	0.370
F Statistic	28.275*** (df = 3; 2376)	297.657*** (df = 4; 2375)	52.783*** (df = 24; 2324)	28.523*** (df = 50; 2298)

Additional controls: sex, high school type, high school final mark, standardized credits, dummies for year of enrolment.

Note:

*p<0.1; **p<0.05; ***p<0.01

As expected, grade point average is still a significant variable in explaining the variability in math grades and every additional point in students' GPA increases their grades by approximately 1 point. Students who pass the exam in January earn on average 0.54 points more than students who decide to delay the exam or do not pass it at the first attempt and are forced to retake it, and the difference is statistically

significant.⁸ This is in line with previous findings in the literature, see for example Cappellari et al. (2012), who show that the longer students of Economics wait to take the mathematics exams, the less likely they are to obtain high grades.

The model in column (3) checks the robustness of our findings with the inclusion of several additional controls: sex, type of high school attended and final mark, number of standardized credits achieved and dummies for students' year of enrolment. Results obtained are similar to those in column (2), the magnitude of the interaction term increases to 1.2 and significance also increases. The only significant additional covariate is the dummy for "licei" that are high schools typically chosen by students who plan to go to university, and these students obtain on average 0.65 points more.

In the fourth column we add course fixed effects, to take into account the different tracks chosen by students in the control group, and time fixed effects since we consider students of the two waves 2011 and 2012. Results robustly confirm the positive effect of online activity.⁹ The model explains 37% of the variability in the data, and adding fixed effect increases the models' explanatory power by approximately 2%, compared to the specification in column (3).

In the previous regressions we include as treated students who passed the math exam within the January session (sub-sample $T_{1,2}$) only students who defined themselves as "fairly active" or "one of the most active". We perform a second set of regressions including also students who defined themselves as "not very active" or "one of the least active", so all students who filled in the survey, see Table 7.

As shown in column (4) the interaction term $January_i * T_i$ is still significant but, as expected, the magnitude drops to 0.94. This interestingly points out that also students that did not defined themselves as active, but perhaps content themselves to visualize the page, earned higher grades. Another possible interpretation is that the Facebook page generated positive spillovers and also students who did not directly use the page indirectly benefited from it, for example, because they studied with their colleagues that were active on the page. In the previous set of regressions, we included in the

⁸We do not record failed attempts to take the exam. If a student did not pass in January, and passed in June, his grade is simply recorded in June.

⁹The estimated coefficient for the effect of being in the T group is -1.941 but this is because the variable interacts with the course fixed effect that identifies the same subgroup, and its estimated coefficient is 1.898. Therefore the marginal effect of being in the T group is basically 0, as in column (3).

treated group all students that filled in the survey, regardless on whether they defined themselves active or not.

Table 7: Difference-in-difference for effect of activity on math grade (all T sample).

	<i>Dependent variable: math grade</i>			
	(1)	(2)	(3)	(4)
January	1.546*** (0.189)	0.528*** (0.159)	0.413** (0.162)	0.286* (0.161)
T	0.902*** (0.264)	0.316 (0.219)	0.045 (0.265)	−1.279 (0.837)
January*T	0.261 (0.389)	0.457 (0.321)	0.939*** (0.352)	0.943*** (0.350)
GPA		1.069*** (0.031)	1.078*** (0.039)	1.123*** (0.039)
Constant	21.075*** (0.166)	−3.707*** (0.735)	−2.094 (3.061)	−3.197 (3.017)
Additional controls	NO	NO	YES	YES
Course FEs	NO	NO	NO	YES
Time FEs	NO	NO	NO	YES
Observations	2,501	2,501	2,470	2,470
R ²	0.038	0.346	0.365	0.393
Adjusted R ²	0.037	0.345	0.359	0.380
F Statistic	33.090*** (df = 3; 2497)	330.586*** (df = 4; 2496)	58.550*** (df = 24; 2445)	30.672*** (df = 51; 2418)

Additional controls: sex, high school type, high school final mark, standardized credits, dummies for year of enrolment.

Note:

*p<0.1; **p<0.05; ***p<0.01

Nevertheless, potentially also students who decided not to fill in the survey could have benefited, directly or indirectly, from discussions on the Facebook page. As a final and sharp robustness test, we perform a set of regressions in which we include in the sub-sample $T_{1,2}$ of treated students all students who passed the exam in the January session of the two waves studied, 2011 and 2012, retrieving this data from the

administrative records; estimates are reported in Table 8.

Table 8: Difference-in-difference for effect of activity on math grade using administrative data also for T_{12} , so including also students who might have not attended.

	<i>Dependent variable: math grade</i>			
	(1)	(2)	(3)	(4)
January	1.525*** (0.191)	0.477*** (0.158)	0.345** (0.162)	0.267* (0.161)
T	0.886*** (0.267)	0.272 (0.219)	-0.049 (0.265)	-2.272** (0.935)
January*T	-0.322 (0.335)	0.187 (0.274)	0.553* (0.314)	0.513* (0.312)
GPA		1.098*** (0.030)	1.105*** (0.037)	1.137*** (0.037)
Constant	21.098*** (0.167)	-4.344*** (0.707)	-1.688 (3.036)	-2.595 (2.992)
Additional controls	NO	NO	YES	YES
Course FEs	NO	NO	NO	YES
Time FEs	NO	NO	NO	YES
Observations	2,704	2,704	2,647	2,647
R ²	0.032	0.354	0.367	0.391
Adjusted R ²	0.031	0.353	0.362	0.382
F Statistic	29.763*** (df = 3; 2700)	369.544*** (df = 4; 2699)	66.231*** (df = 23; 2623)	44.043*** (df = 38; 2608)

Additional controls: sex, high school type, high school final mark, standardized credits, dummies for year of enrolment.

Note:

*p<0.1; **p<0.05; ***p<0.01

The interaction term confirms the positive effect of online discussions on performance but, as expected, the magnitude of the effect is smaller than in the previous specifications. The interaction term in column (4) shows that treated students earn on average half additional point and the estimate is statistically significant at 10 percent level. In this specification, we include students who perhaps attended the classes, participated and benefited from online discussions but simply did not fill in the survey.

Moreover, we also include students who maybe did not attend classes or use the Facebook page, because they did not know about it or are enrolled in previous academic years. If this is the case, this set of regressions is under-estimating the true effect of online discussions and the coefficients should therefore be considered as lower-bounds.

A possible threat to the validity of the causal interpretation of the difference-in-difference estimates is the following. In the design of the quasi-natural experiment we use the assumption that, if online discussions had an effect on performance, it is only for students who passed the exam within the January session, and use the following sessions as a post-experimental period. This basically means assuming a *short-run* effect. It could instead be that online discussions also have a *long-run* effect and also students who took longer to pass the exam still benefited from the Facebook page. We believe this is a minor issue and, given the difference-in-difference strategy, if this is the case we would be under-estimating the true effect of online discussions.

A second possible danger to the validity of our estimates is that we cannot exclude that also students in the control group visualized and potentially benefited from the Facebook page, perhaps hearing about it from their friends and colleagues in the treated group. Anyone with internet access could visualize the page with no need to be a Facebook user or to register on the page. However, if this actually occurred, and the effect of Facebook is positive, also in this case we are under-estimating the true effect and our estimates should be considered as a lower bound for the effect of Facebook activity on performance.

7 Concluding remarks

In this paper we assessed an experiment that consisted in providing online support to live lectures of a traditional mathematics course for undergraduate students. We exploit a newly constructed dataset obtained merging information collected with a survey and university records. The data provides us two cohorts of comparable students, but only one group has been exposed to the online activity on Facebook. This design allows us to use a quasi-experimental approach, overcoming some of the almost unavoidable concerns related to selection bias. As a result we are able to assess the effect of Facebook use on students' math grades by using a difference-in-difference approach. To the best of our knowledge, this is the first paper that uses a quasi-experimental design to assess

the effect of Facebook use on academic performance.

The students greatly appreciated the opportunity to have such support but it is more interesting to appraise the effects on grades, which are important (albeit non-unique) indicators of students' performance. Regression models on the treated group only show that, after controlling for skill as measured by the GPA and other variables, a few measures of activity (but not all) are positively correlated with the grade. In particular, students declaring that the online support was very useful (10/10 on a Likert scale) indeed get 1 additional point on average and the frequency of visualization monotonically increases the probability to have a passing grade.

Taking advantage of the fact that parallel and formally identical courses were offered in another town at the same university, we estimated a difference-in-difference model and compare the treated group with similar students with no availability of the online support page. This procedure has the capability to net out some possible biases in the samples and reduce self-selection effects. The main result is that the members of the treated group gain on average about one extra point (out of 30) in the math exam, when compared to other students of the same university who appear to be similar in all dimensions but took the math exam without the Facebook page.

Our results also suggest a possible differential effect due to students' individual attitude. Active students who read and oftentimes wrote posts performed better than the students who mainly read the content, but the difference is small and not statistically significant. However, the fact that the group to whom they belong as a whole has better performances suggests that the page might be more effective for low performing students, that can benefit from interaction and information posted and shared by more active and skilled colleagues.

Other studies have shown that several alternative teaching approaches using, say, videos or blended lectures or other technical and pedagogical devices, do not change much the performance of the students as far as grades are concerned. We feel that our work is in line with such previous findings: even if we do find a significant effect, from the practical point of view, its magnitude is limited and close to $1/30$. This is less than the gap needed to move, say, from B to B+, using another familiar grading scale. In retrospect we believe this is a reasonable amount for the net improvement that can possibly be gained from activity online, as the bulk of competencies and comprehension still is (and always was) due to hard, individual and mainly *offline*, work to understand,

elaborate and digest reading material and assigned problems or tasks.

We are well aware that these results should be taken as suggestive rather than conclusive and this paper could be improved in several directions. Although we are confident that we got a representative sample of the overall population of students, more research on larger representative samples would allow us to increase the external validity of results and dig into heterogeneous effects. Moreover, these results ultimately concern undergraduate economics students taking a mathematics course, and caution is needed to generalize immediately to different types of students and studied subjects.

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