The effect of using YouTube as a didactitc support on microeconomy's grades

El efecto de usar YouTube como apoyo didáctico en calificaciones de microeconomía

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Keywords
Education, YouTube, online didactic resources, impact evaluation, econometry

ABSTRACT

Recent research has shown that using YouTube videos as teaching material improves student's grades in Online Master programs. This article shows that the use of videos for undergraduate students in face-to-face programs improves by 3.54% the average grade of students treated. A procedure based on Randomized Controlled Experiments (RCT) was followed, where the treatment is controlled by different observable characteristics about the high school education of the students, their scores on university admission tests, their access to internet connection and their study habits. These results confirm the importance of the use of new technologies in face-to-face learning at undergraduate programs.

Palabras clave
Educación, videos educativos, recursos didácticos en línea, evaluación de impacto, econometría

RESUMEN

Investigaciones recientes han mostrado que la utilización de videos de YouTube como material didáctico mejora las calificaciones en programas de Maestría en línea. En este artículo se demuestra que el uso de videos de YouTube para estudiantes de licenciatura en modalidad presencial mejora en 3.54% la calificación promedio de los estudiantes tratados. En el estudio se siguió el procedimiento de experimentos controlados aleatorizados, en el cual se controla por distintas características observables acerca de la educación a nivel preparatoria de los estudiantes, su calificación en exámenes de admisión a la universidad, su acceso a conexión de internet y sus hábitos de estudio. Estos resultados confirman la importancia de la aplicación de nuevas tecnologías en modalidad presencial para programas de Licenciatura.

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INTRODUCTION

Education is an ever-changing topic since educational institutions seek optimal quality of educational services with better learning for students (Llorente, 2008). Some educational institutions, in search of educational quality, involve all the stakeholders intervening in the educational process, in both the ongoing revision of educational programs and the ways of transmitting their contents (BUAP, 2007).

Different authors (Coll, 2004; Cabero, 1996, 2008, 2010; Colina, 2008) highlight information and communication technologies (ICTs as a resource that efficiently contributes to improving educational quality including infrastructure and teacher training (Lugo, 2010). In this sense, the incorporation of ICTs in classrooms is considered as providing opportunities to create learning environments based on a quality, student-centered, attractive, interactive, economic, efficient, accessible, flexible and meaningful design (Coll 2004; Cabero and Colina, 2008; Lugo, 2010).

Fandos, Jiménez and González (2002) point out that ICTs allow creating new online spaces that help overcome barriers referring to the overlapping of space and time which until now was essential between teachers and students immersed in the teaching-learning process. Wagner (2001) and Garza (2001) on the one hand, observed that technological learning environments, besides being efficient, convenient and motivating, promote the development of knowledge and skills in students in a virtual context that can take place on Internet platforms where students and teachers interact, as well as simulate the interaction that exists in a face-to-face classroom. In both cases, the important thing is to generate learning, construed "as a change in the meaning of their experiences".

Recently, Rodríguez and Fernández (2017) established that the implementation of videos on YouTube as support material in a statistics course for Latin American students of an online master's degree generated a positive impact on the students' grades. The authors attributed this result to the improvement of the students' comprehension of the content of the subject. The foregoing results are quite peculiar since online programs can either attract students who know how to best use ICTs, or motivate postgraduate students better than other type of students; hence the question arises as to whether the application of videos on YouTube would produce similar results in students of other learning modalities or educational levels.

This paper aims at studying the use of videos on YouTube as learning material for students at the bachelor's degree level, in the face-to-face modality of a course in microeconomics at a university located in Puebla, Mexico. More specifically, we measured the causal effect of using didactic material based on the YouTube platform on the grades obtained for the subject mentioned above. Our study differs from that of Rodríguez and Fernández (2017) since in our study, we analyze undergraduate students who might have a lesser motivation than those enrolled in a master's degree or students in a face-to-face modality. These students might have lesser knowledge in using ICTs in comparison to online students.

In our study, we have a tighter control on the comparability of students since all of them belong to the same academic generation and face the same infrastructure conditions in their university, contrary to Rodríguez and Fernández (2017) research, where students may be in different countries and, thus, face different infrastructure conditions depending on the region where they connect to their online platforms.

To find the causal effect, we followed the randomized controlled experiments (RCE) (Lazcano, Salazar and Gutiérrez, 2004; García, 2011; Baker, 2000; Gertle *et al.*, 2011; Navarro, 2005; Moral-Arce, 2014). We found that the use of videos as didactic materials improved the grades of the students under study by 36%, and a confidence level of 1%.

This paper is divided into the following six sections: In the first, we review the literature on the relation of teaching-learning process and ICTs as well as quantitative empirical research. In the second, we address the RCEs and the reasons that led to the identification of that causal effect. In the third we describe the estimated RCEs and the empirical model and formulate an equation that links the academic achievement with the observable characteristics and their participation in the RCEs. In the fourth, we specify the characteristics of the population observed in both the control group and treatment group; hence the importance of determining if the necessary assumptions for the application of an RCE are met in the population under study. In the fifth, we present the results of the RCE and, in the sixth, the conclusion.

THEORETICAL CONSIDERATIONS

It is not an easy task to determine the impact of ICTs in the teaching-learning process given the existence of at least three statistical problems. First, the problem of selecting observable and non-observable characteristics in students since the success of ITCs depends on every student's individual skills (López, 2013), which can be associated to the resources available to the student during his/her academic formation, the parental style by which he/she was reared, the education and condition of his/her parents' employment activity, among others (Cuecuecha, 2017).

The second problem resides in selecting observable and non-observable characteristics of schools since the adoption of technologies among different schools does not occur randomly; for example, some schools may have greater resources to invest in ICTs and incorporate them in their teaching-learning processes. The third problem we face is that the heterogeneity in information technologies may be difficult to measure: if the specific nature of the information technology being used is unknown, the real impact of ICTs can be measured erroneously.

Therefore, the RCT uses videos on YouTube exclusively and is applied to students of a same university, faculty, bachelor's degree and generation. In order to control the observable and non-observable characteristics of the students, we followed two strategies; first, we applied a survey in the community of students belonging to the faculty of their undergraduate studies to determine the existence of the selection of students based on their studies of choice within their faculty; the purpose of this survey was to assess the probability of choosing the bachelor's degree in question.

The second strategy consisted in a methodology of difference in differences to analyze the impact of the treatment exclusively on the change observed in grades before and after the treatment. 89 students participated of which 41 belonged to the group in reference. The treatment was divided into three stages; in the first, all the students received traditional material; in the second, the group treated received material based on YouTube videos; in the third and last, all went back to using traditional material. At the end of every stage, we administered exams to measure the students' performance. In this study, students could not choose the professor or the subject section in which the intervention was used.

Based on the evidence that the selection in the non-observable is minimal, we decided to use data randomized matching techniques (RMS) to find the impact of the intervention not only on the mean but also throughout the distribution.

Notwithstanding the methodologies followed to obtain the causal effect, there are non-observable elements that could generate assessment biases; for example, if the students modified their enthusiasm in studying a subject, maybe as a consequence of using YouTube, we could assign the impact to the use of ICTs when in fact, it is only the enthusiasm of the students to spend hours studying that varied. This research was guided by the hours the students reported having studied in the survey; however, if, at the time of the experiment at the level of enthusiasm, there would have been non-observed variations, we could have noted biases; hence, the possibilities of extrapolating the results of the experiment to other environments are limited. Then the recommendation would be to apply RCEs to other levels of education and to other subjects in order to validate the results obtained in our study.

RELATION WITH THE LITERATURE

There are several studies that seek empirical evidence of academic achievements obtained from the efficient use of ICTs during the teaching-learning process. First, we highlighted the studies evaluating the effects of ICTs understood as *hardware*. Alderete and Formichella (2016) evaluated the Connect Equality program applied in Argentina in 2012 which consisted in providing 15-year old students notebooks in order to determine the result-based-performance of the PISA test (Program for the International Student Assessment) in mathematics, sciences and language. The study measures the propensity of the student to participate in the program. It was found that the school socio-economic level and the Internet availability at home have a significant and positive impact on the probability of the student to participate in the program.

On the other hand, the students who repeat classes and whose parents are unemployed have significantly less probability in participating in the program. The authors conclude that the non-observable characteristics are equal to the performance cast by the program; hence, they point out the need to provide an academic purpose to donating notebooks.

Along these lines, Machin, McNally and Olmos (2006) measured the effects of the change of policy in allocating resources to invest in ICTs on the educational results of elementary and high schools in England in 2001. To do so, they first measured whether the effect in allocating resources for ICTs per student was different for elementary schools than high schools. They found a positive effect in elementary schools; afterwards, they measured the effect on allocating resources on the average grades in mathematics, language and sciences in 11-year-old students and they noticed a positive and significant relation between the financing of ICTs per student and the performance in English and Sciences, while in Mathematics, the relation was positive but not significant.

Secondly, we have studies that assess ICTs as software. As of 2005, in Guyaquil, Ecuador, Carrillo, Onofa and Ponce (2010) analyzed the More Technology program which consisted in providing every elementary school with four computers that contained a *software* designed to facilitate the learning of mathematics and language of the third and fifth graders. The authors observed a positive impact on the scores of the mathematics test and a negative impact regarding language.

Angrist and Levy (2002), on the other hand, measured the effect of the Tomorrow-98 program developed and implemented in Israel since 1994 on the grades obtained in Mathematics and Hebrew. The program provided Jewish elementary and high schools with a *software* program providing a computer-assisted instruction (CAI) to students of the fourth and eighth grades in order to identify the effect of the program. They took into consideration the characteristics of the schools and of the students as well as the use of CAI.

Angrist and Levy (2002) found that the program improved the scores of the fourth graders in mathematics but found little evidence that it improved the scores of the eighth grade students; hence, they concluded that the CAI did not contribute significantly to improve the students' grades.

Lastly, Rodríguez and Fernández (2017) analyzed the use of videos on YouTube as a resource of didactic content in Statistics for students enrolled in the master's degree in Business Administration, distance education modality. The study consisted in providing a group of students with videos as didactic material on a weekly basis. As of the second term, the authors found that the group using the videos as support material obtained a one-point higher grade in comparison to the group that used traditional material.

ASSESSMENT OF THE IMPACT AND THE RCTs

As of the middle of the past century, statistical methods proved to be very useful. In the health sector, they started being used to verify the efficacy of new treatments or drugs and their effects on patients suffering from chronicle ailments (Lazcano *et al*., 2004). The efficiency of these quantitative methods soon brought other sciences to adopt this type of impact assessment. The assessment of public politics is the field that has most benefited from the statistical tool to verify the effects of applying public policies on a target population (Ravillion, 2008).

The impact assessment is a statistical method that measures the effects in the conditions of people that can be attributed to a project, program or specific policy (Navarro, 2005; Baker, 2000; Moral-Arce, 2014); it focuses on the magnitude of the effects generated and its causality with the intervention. The effects may be positive when they improve welfare conditions, and negative when the changes deteriorate them. These effects may be due to observable factors such as home, sex, marital status, and other characteristics; and non-observable such as moral values, motivations and personal interests, among others.

The main characteristics are the verification of the hypothesis and the group comparison. The first one explains the relation between two or more independent variables (cause) and dependent variables (effect), while the second uses a counterfactual scenario to determine the causality between the intervention and the changes experimented by those receiving the benefits. The situation of those receiving the benefits should be understood as a counterfactual scenario if they had not participated in the intervention.

It is worth highlighting that this argument cannot be directly observed. Gertle *et al*. (2011) point out that it is necessary to identify a comparison group with the same characteristics of the treatment group in at least three aspects. Both groups must be identical in the absence of the program; the groups must react in the same way to the program; and neither group can be exposed differently to other interventions during the assessment period.

The counterfactual scenario can be determined by using experimental or almost experimental designs. The first are considered as the most solid and robust (Baker, 2000; Navarro, 2005). Lazcano *et al*. (2004) highlight the control the researcher has over the selection of the population, treatment administration and form in which the observations are achieved. The randomization guarantees that, in average, the differences between these groups are due solely to the fact of participating or not in the program since all the factors observed and not observed during the selection process have been eliminated and the incidence of other independent variables associated with the impact variable (dependent variable) and the participation in the program has been controlled; hence, the comparison group provides the information of what would have occurred to those receiving the benefits if they had participated in the intervention.

There are two types of RCTs that allow establishing the cause-effect relations of an intervention. On the one hand, there are the substitution designs, and on the other, crossed designs. The first are based on collecting a sample when changing treatment A for another alternative treatment B. In this type of RCTs, the study subjects are divided into two groups: one is called the control group and the other, the treatment group. Both groups receive treatment A during the first stage. In the second stage, the control group continues receiving treatment A, while the control group is intervened with the alternative treatment B. In the third stage, both groups receive the same treatment A. Finally, the observations on treatments A and B are compared for every stage of the intervention.

In the case of crossed designs, group 1 receives treatment A during the first stage and group B in the second stage. Group 2 receives the group 1 treatments in reverse order. In this type of design, every subject is used as his/her own control. The RCT presented in this paper was designed to be an experiment with substitution design.

EMPIRICAL MODEL

In order to measure the causal effect of an intervention (P) on a result (Y), we basically consider that (P) is a binary variable that acquires the value of 1 if the subject took the treatment and 0 if he did not. The non-observation of the counterfactual arises from the fact that an individual cannot belong to both groups.

Table 1. Fundamental of the causal inference

	Y_0	Y_1

P=0	Observable	Non observable
P=1	Non observable	Observable

Source: Self development.

In this paper, we will use the double difference methodology to assess the average effect of the subjects treated and the RMS. The Difference in differences (DD) consists in applying a double difference, i.e., assessing the counterfactual of the change of the result for the treatment group by calculating the change of the result for the comparison group. This method allows us to take into consideration any consistent difference in time between the treatment and control groups. The DD strategy can be formulated in a linear regression model to contrast the hypothesis over the estimates, or include other control variables using a binary variable (D) that identifies the variable of interest in two different moments: one called "before" that observes the variable of interest before applying the treatment, D=0, and the other called "after" that observes the variable of interest after applying the treatment, D = 1.

(1) $Y_{P,D} = \beta_0 + \beta_1 D + \beta_2 P_i + \delta P_i D_i + \mu_i$

Where $\delta P_i D_i$, the interaction coefficient, represents the difference in differences method and is calculated as follows:

(2) $DD = E(Y_{11} - Y_{01}) - (Y_{10} - Y_{00}) = ATE + E(Y_{11} - Y_{10}) - E(Y_{01} - Y_{00})$

This means that the DD method is a double difference. The first is the expected value of the treated and control groups after the intervention. The second is the expected value of the groups before the intervention.

The RMS method consists in forming a control group based on similar individuals as those of the treatment group among a group of untreated individuals. The validity of the matching is based on two hypotheses. The first, the conditional independence hypothesis, requires that there be no systematic differences between the treated and untreated agents once the observable values has been conditioned; by controlling the individuals for their observable characteristics in every subgroup, we will have a treatment independent from the results and administered randomly. The second, the common support hypothesis, requires the existence of a certain probability between the treated and untreated subjects that will receive a treatment. Similarly to Alderete and Formichella (2016), we indicate the following matching methods:

- The closest neighbor (ATTND): an untreated student *j* is chosen to be the contractual student *I,* in such a way that:

$P_{o,j} = min_j \mid P_i - P_j \mid$ is the control student j chosen from the untreated group. This j student minimizes the difference between his *propensity score* (PS) and that of the treated student.

- Kernel estimator (ATTK), according to which the treated students are matched with the weighted average of all the control students with weighing inversely proportional to the distance between the *propensity score matching* (PSM) of the treated students and the untreated.
- Stratification (ATTS) allows the matching between the treated and untreated students based on a variable containing a block identifier (stratum) pertaining to the registry of the common support zone. The common support region implies considering in the estimate of the average effect of the treatment in the treated students (ATT), the students pertaining to the specific range per minimum and maximum *propensity scores* of the students of the treatment group.

While these are the most commonly used statistical methods, it should be noted that the literature on the topic is even more extensive. We, however, have the necessary elements to describe the empirical model that relates academic achievement with the observable characteristics in this experiment.

DESCRIPTION OF THE CONTEXT IN WHICH THE EXPERIMENT IS CONDUCTED

The experiment was conducted in a university in the State of Puebla, Mexico, with students of the bachelor's degree in International Relations (BIR) of the fourth semester, during the fall of the 2017 academic year, in the in-class modality. All the students applying to the university had to take an admission examination and, in this experiment, they were required to give us their scores which were included as a control variable. The admission also considered if the subjects had graduated from high schools pertaining to the academic units that make up the university, since those students have a direct admission pass to the university (considering their GPA and the score obtained in the admission exam). It should be mentioned that a fourth-semester average student take six subjects in a semester; these subjects have been assigned by the academic authorities of the program. The students cannot choose subjects, timetables or sections, since a subject is given at the same timetable by different professors.

DESCRIPTION OF THE EMPIRICAL MODEL

We propose an empirical model that relates the BIR students' academic achievement in the in-class modality participating in the RCT [ECA, Spanish acronym] and observable characteristics as follows:

(3) $Final_i = \Phi(\beta_1 X_{age} + \beta_2 X_{private} + \beta_3 X_{highschoolpass} + \beta_4 X_{score1i} + \beta_5 X_{score2i} + \beta_6 X_{Timestudy1} + \beta_7 X_{Timestudy2})$

where the $Final_i$ variable is obtained in the course; it takes values from 0 to 10; P being the participation in the treatment; it takes values of 1 if the student participated and 0 if he did not; X_{age} is the student's age; $X_{private}$ is the type of studies at high school level; it takes the value of 1 if the studies were pursued at a private school, and 0 at a public school; $X_{highscholpass}$ has the value of 1 if the studies were completed at a high school from an academic unit of the university and 0 in any other case; $X_{score1i}$ is the score obtained in the admission examination; it ranks from 550 to 650 points; $X_{score2i}$ i the score obtained ranking from 650 to 750 points; $X_{Studytime1}$ are the hours spent studying per week for the first partial exam; $X_{Studytime2}$ are the hours spent studying per week for the second partial exam.

The previous model is valid under the assumption that the treatment be at random and that the observable variables introduced in the model allow controlling all the students' observable characteristics. As mentioned earlier, not to pursue this assumption, it is possible to estimate a double difference model which would eliminate the fixed factors in the students. This model can be explained in equations 1 and 2 in order to identify the effect in the grades observed after using the treatment. We present this empirical model in equation (4):

(4) $dtest_i = \beta_0 + \beta_1 X_{age} + \beta_2 X_{private} + \beta_3 X_{highschoolpass} + \beta_4 X_{score1} + \beta_5 X_{score2} + \beta_6 X_{material} + \beta_7 X_{materialb} + \beta_8 X_{studyhours} + \beta_9 X_{studyhours} + \beta_{10} P + \mu$

where *dtest* is the difference in the grades obtained in the second partial exam in regard to the first; *dtest1* is the difference between the final grades in comparison with the second partial exam; and *dtest2* is the difference between the final grade in reference with the grade obtained in the first partial exam.

Lastly, to analyze the treatment not only in the entire distribution and not only in its average, we applied the RMS techniques which we explained previously.

DESCRIPTION OF THE POPULATION

The population under study refers to students of the BIR in the in-class modality that took the Microeconomics course during the fall of 2017. Said population is described in Table 2, in which we observe that it consists of 84 students divided into two groups: a treated groups referring to 41 students provided with videos as didactic material, and an untreated group made up of 43 students that did not receive any videos, drawn from the observable variables.

Table 2. Description of the population

Population	Untreated	Treated	Total	Difference untreated/treated
Partial 1	6.65	8.3	7.48	1.69*
Partial2	7.1	8.9	7.98	1.81*
Final grade	6.9	8.9	7.88	1.99*
Age	20.02	20.12	20.07	0.09
Private education	0.39	0.36	0.38	-0.02
High school automatic pass	0.16	0.19	0.17	0.03
Score1	0.13	0.12	0.13	0.002
Score2	0.62	0.6	0.61	0.01
Study time1	1.25	1.51	1.38	0.25
Study time2	1.69	2	1.84	0.3
n	43	41	84	

* Significant at 1%
Source: Self development.

At a glance, there is a difference in the final grade between the treated and untreated populations. The average of the first partial exam for the untreated group was 6.65, while 8.3 for the treated group. The average for the second partial exam for the untreated group was 7.1 and 8.9 for the treated group. It should be mentioned that we did not studied the statistical significance of these differences until the following section since it must be controlled by the observable characteristics of the students.

39% of the students of the untreated group come from a private high school and 36% of the treated group from a private high school. 13% of the untreated group is in the Score1 range as well as 12% of the treated group, while for the Score2 variable, 62% of the untreated group is within this range. In regard to the untreated group, we observed that they dedicated 1.25 hours of study per week for the first partial exam, while the treated group spent 1.51 hours studying weekly for the same exam. Likewise, the untreated group dedicated 1.69 hours of study per week for the second partial exam and the treated group, two hours of study in average per week.

POSSIBLE SELECTION BIASES IN OUR SAMPLE

The application of the RCT [ECA, Spanish acronym] methodology is based on the assumption that the population under study was randomized on a population that, from the statistical standpoint, was similar in its observable characteristics. In this study, we include the treatment of students of the same faculty, bachelor's degree and academic generation, which casts a homogeneous population of observable characteristics; however, there can be changes such as age, high school educational background, hours of study and maybe the resources available to them given their socioeconomic conditions.

These differences in the observable characteristics are intended to be obtained based on the survey conducted with the students. There could also be other implicit selection biases since every student may have a different propensity in participating in the treatment derived from his/her personal interest for the BIR or for a possible choice to take classes that were selected to be treated. In this section, we show that there is evidence that the BIR students are different from the average students of the faculty under study. We have also found that there is no selection bias to participate in the treatment.

To determine if there was a selection bias for being a BIR student, we conducted a survey with the students of the 2016 generation of the Bachelors' degrees in Political Sciences, Criminology and International Relations. The questions were on general aspects such as sex, age, type of high school (public or private), if the high school had a direct pass to the university, admission score and connection to the Internet which is divided into a home connection, mobile and their use of the Internet. We took a Probit model which dependent variable has the value of 1 if it is a BRI student, and the value of 0 in any other case. The model is expressed as follows:

(5) $\Pr(Y=1 \mid X_i) = \varphi(\beta_0 + \beta_1 X_{age} + \beta_2 X_{private} + \beta_3 X_{highschoolpass} + \beta_4 X_{score1} + \beta_5 X_{score2} + \beta_6 X_{materiala} + \beta_7 X_{materialb} + \mu)$

where $\Pr(Y=1 \mid X_i)$ is the probability of studying the BIRl; $X_{materiala}$ is the student's preference for traditional didactic material such as books, magazines, scientific papers; $X_{materialb}$ is the student's preference for didactic material based on ICTs; μ is the non-observable variable. The other variables were already explained.

In Table 3, we observe that, to the exception of having studied in a high school with automatic pass to a university, and having obtained the Score1, all the variables are not statistically significant. The two variables mentioned reduce the probability of studying the BIR and are significant at 5%. The model as a whole is statistically significant at 1%; while the pseudo R^2 can explain 6.4% of the data variation. The estimates show the control of the probability of studying the BIR as well as without said control.

Table 3. Preference model to study the bachelor's degree in International Relations

Preference model to study BIR		
Variables	Probit Estimates	Standard Errors
Age	-.004418	.0737727
Private	.1684801	.229565
High school pass	-.6795953*	.2454751
Score1	-.8968417*	.323078
Score2	-.2222637	.2091178
Materialb	.2326445	.2152165
Materialc	.2964923	.2718475
_cons	.2786243	1.47864
R^2	6.4%	
N	187	
Test LR (maximum Plausibility) chi2 (6)		16.46
Value p	0.0115	

* Significant at 5%
Source: Self development.

Table 4 includes the estimate of a probability model to determine the randomization of the treatment. This estimate also included the students that were not enrolled in the BIR but are part of the same faculty. Model (6) shows the estimated equation which dependent variable is the participation in the treatment and the independent variables are the same as those previously mentioned:

$$(6)\ \Pr(P = 1 \mid X_i) = \varphi(\beta_0 + \beta_1 X_{age} + \beta_2 X_{private} + \beta_3 X_{highschoolpass} + \beta_4 X_{score1} + \beta_5 X_{score2} + \beta_6 X_{materiala} + \beta_7 X_{materialb} + \varepsilon)$$

where $\Pr(P = 1 \mid X_i)$ is the probability to participate in the treatment and are the non-observable elements in the treatment equation.

In Table 5, we notice that none of the variables is statistically significant and neither is the model as a whole. This shows that the variables selected allow to determine the existence of a selection bias for the field of studies (BIR) chosen; however, there is no selection bias in the treatment.

Table 4. Randomization Model of the treatment

Preference model to study BIR		
Variables	Probit Estimates	Standard Errors
Age	.0206427	.0788509
Private	.131084	.2409454
Highschoolpass	-.3171593	.276501
Score1	1.095481	.9372713
Score2	.1371527	.234669
Materiala	.1557351	.2371463
Materialb	.1492576	.3002784
_cons	-1.330112	1.47864
R^2	2.3%	1.603311
N	189	
LR Test (maximum plausibility) chi2 (7)		4.61
Value p	0.7079	

Source: Self development.

RCT RESULTS

Table 5 shows that the treatment variable is significant at 1%, and an effect of 1.54 grade units is obtained; this is the equivalent of a 17% raise in the grade obtained before the treatment. It also shows that the hours of study are statistically significant at 1% and increase the grade of .60 points for the first partial exam and of one point for the second exam. The age variable is significant at 10%, and it reduces -.14 points the grade obtained. This estimate may be biased given the assumption that of a random treatment and that it is not correlated with the students' non observed variables. In this equation, this cannot be asserted since we have not applied the difference between the "before" and "after" treatment. This will be addressed in the next estimate.

Table 5. Model of the effect of ICTs on the final grade

Treatment	1.532827** [.2187623]
Age	-.140493* [.0729101]
Private	.3076795 [.2244591]
Highschoolpass	-.1098169 [.3797313]
Score1	-.086287 [.3718612]
Score2	-.215147 [.2276607]
Studytime1	.602009** [.1475319]
Studytime2	1.000012** [.1478233]
Cons	7.293339** [1.527952]
N	82
F	32.83
Prob > F	0.0000

R^2	75%
MSE	.91494

* Significant at 1%
** Significant at 10%
Source: Self development.

The estimates for the DD model are shown in Table 6 in which we notice that the dtest column of the hours spent studying and the high school pass are statistically significant; however, as we carry out the dtest1 and dtest2, we observe that the high school with direct pass variable is no longer significant. On the other hand, the private studies variable is significant at 5%. This suggests that the students' academic achievement is directly affected. Likewise, we notice that the treatment is statistically significant only when we compare the first exam with the final one, and the impact is a grade of .30 points, which represents a grade increase of 3.54%.

Table 6. DD Model

Robust DD Model, with control for being in the BIR			
Variables	dtest	dtest1	dtest2
Age	-.0920688 [.0730705]	.0516805 [.0814963]	-.0403882 [.0617792]
Private	.2627439 [.2139701]	.1101264 [.2110114]	.3728703** [.1657878]
Highschoolpass	.5702511* [.32893]	-.2639009 [.2806984]	.3063502 [.2680088]
Scoreb	.0630596 [.2979562]	-.2043366 [.2957149]	-.141277 [.2568983]
Scorec	-.13 38628 [.2341151]	-.0627404 [.2001688]	-.1966032 [.1988149]
Treatment	-.0132961 [.2253785]	.3149593 [.2110734]	.3016632** [.1593557]

Xtimeperhourweekly	-1.359175*** [.1529444]	.6591457*** [.1232337]	-.7000297*** [.1252032]
Xtimeperhouweekly	1.220483*** [.1488297]	-.7758477*** [.1229608]	.4446357*** [.1144328]
_cons	1.907058 [1.547121]	-.7235157 [1.693993]	1.183542 [1.254534]
R^2	67.7%	43.3%	45.2%
N	82	82	82
F	15.53	8.30	4.85
Prob > F	0.0000	0.0000	0.0001
Root MSE	.84078	.84405	.67205

* Significant at 10%
** Significant at 5%
*** Significant at 1%
Source: Self development.

Now, we will carry out a robustness model using the RMS method to identify the effect of using YouTube videos on the BIR students' academic achievement. Table 7 shows the difference in the academic achievement among students that received the treatment and those that did not, and it is statistically significant for two of the four techniques used. In both cases of significant effect, the treatment indicates 5%. The estimated causal effect is greater than the one obtained through the DD technique. This implies that, while measuring the impact on the sample average, there was a drop in the bias and, while measuring the effect along the grade distribution, it was possible to identify a greater impact.

Table 7. ATT estimate

Test	PSM	Treated	Controls	ATT	t of Student
dtest2	ATTND	41	26	0.387 [0.246]	1.585
dtest2	ATTR	27	36	0.600 [0.308]	1.947*
dtest2	ATTK	41	42	0.280 [0.207]	1.349
dtest2	ATTS	5	78	0.852 [0.491]	1.734*

* Significant at 5%
Notes: ATT: treatment in the treated students; PSM: *propensity score matching*; ATTND: treatment of those treated according to the Closest Neighbor, a substitution sampling is used; ATTR: treatment in those treated according to radius, a 1% radius was used; ATTK: treatment of those treated according to Kernel; ATTS: treatment in those treated according to stratification.
Source: Self development.

It is important to point out that the ATT estimates were made by taking into account a common support for the treatment as well as the controls. Likewise, we used a substitution sampling; moreover, the standard errors were obtained with *bootstrap* with a thousand repetitions.

FINAL CONSIDERATIONS

In the study carried out through an RCT application, we examined the causal relation between the use of YouTube videos and the students' grades in the Microeconomics course in the field of the BIR, in-class modality during the school cycle corresponding to the fall of 2017.

We found statistical evidence that the private studies and study habits acquired prior to higher education variables are statistically significant in the grades obtained by the students. Therefore, these variables directly affect the academic achievement of the students during their university formation; however, we also found that the use of YouTube videos has an impact even greater than the students' high school background. This implies that the use of ICTs can be a way to improve equity and reduce the gaps among students caused by their socioeconomic origin, which, as shown, may affect the acquisition of education and social mobility (Cuecuecha, 2017).

Lastly, we found statistical evidence that the use of YouTube videos implies a 3.54% average improvement in the grades obtained by the students that were treated; hence, its shows that the YouTube videos, together with an adequate teaching strategy, are a tool that helped the students of Microeconomics to improve their knowledge and learning skills.

These results assert the convenience of using YouTube videos as a learning tool, which had been demonstrated by Rodríguez and Fernández (2017), with students of the online modality of the master's degree. Therefore, our study extends the knowledge by asserting the efficiency of using YouTube videos in students of an in-class modality bachelor's degree.

RECOMMENDATIONS

Given the extensive discussion on the topic of education, we acknowledged the need to conduct a research that would deepen the psycho-pedagogical discussions in which the higher education institution where we applied the RCT is immersed. Our purpose was to determine how the improvement studied in this RCT can be understood in a context of institutional change.

In general, the studies on the application of ICTs in the teaching-learning process must also continue since the technological changes represent an opportunity to improve this process and contribute in such a way that education becomes a mean to reduce the social gaps that exist in our country.

It is important to highlight that to prove that improving grades can be achieved by using YouTube videos prompts an improvement in the individuals' social mobility. It also requires medium-term studies that allow following up on the individuals that have been treated in their professional and economic performance over a long period of time. This type of studies is necessary to determine the benefits of implementing ICTs in the teaching-learning process.

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