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Lights, Camera, School: Information Provision through Television during COVID-19 Times *

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Abstract

This paper examines the effects of providing information on the future benefits of attending school through the airing of a short telenovela titled "Decidiendo para un Futuro Mejor" (Deciding for a Better Future, hereafter DFM) on national television during the COVID-19 pandemic in Peru. DFM utilizes persuasive videos that highlight the advantages of education while providing concrete information on wages and financial aid for higher education. We implemented a randomized encouragement design using phone calls to promote watching TV when DFM videos were screened, with a sample of more than 80,000 families with high school children from 1,978 schools. We investigate the impact of the intervention on dropout rates in 2021. Our findings indicate that the provision of information led to a significant reduction in school dropout rates, with intention to treat effects of about -0.6 pp, which is substantial considering the average dropout rate of 10.2% in the control group. We find stronger effects for students from schools with higher initial dropout and poverty rates. We also find stronger effects for girls, with no observable differences in effects by parental education. These results not only highlight the prevalence of misinformation surrounding education but also suggest cost-effective strategies for mitigating its consequences.

JEL: D83, H52, I28, O18

Keywords: information provision, education, school dropout, television.

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1 Introduction

The role of information frictions has been recognized as a critical factor in understanding various educational decisions, and interventions aimed at reducing these frictions have proven to be among the most cost-effective approaches (World Bank (2023)). Initiated by Jensen2010, who demonstrated substantial impacts of information on educational outcomes, subsequent research expanded in three key areas: the effects of the provision of information about other educational margins, the methods of delivering the information, and the scalability of informational interventions (e.g., Andrabi et al. (2017); Allende et al. (2019); Ajayi et al. (2020); Ainsworth et al. (2023); Hastings et al. (2015); Dinkelman and Martínez A (2014); Bobba and Frinsacho (2022)). Our study contributes to this field by assessing the effects of educational information provision during the challenging circumstances of the COVID-19 pandemic.

This context is crucial for understanding the impacts of information interventions in terms of content and delivery. The COVID-19 pandemic, with its significant economic and social consequences and school closures, increased the risk of children dropping out and experiencing learning losses (UNICEF, 2021). In response, various remote interventions, such as tutoring (Angrist et al., 2022, 2023; Carlana and La Ferrara, 2024), audio messages (Wang et al., 2023), and text messages (Lichand and Christen, 2020), were implemented. Many countries also relied on television for educational content during the crisis (ITU, 2020; UNICEF, 2020). Nevertheless, the effectiveness of television interventions remains unclear.[1]

This paper examines the impact of providing information on the benefits of education to families with high-school children in Peru during the COVID-19 pandemic. We developed a television program titled 'Decidiendo para un Futuro Mejor' (DFM), which was broadcast nationally. DFM uses persuasive videos in a telenovela format, highlighting the advantages of education and providing information on wages and financial aid. The original version of DFM, implemented in 2015 as an in-person program, showed significant effects on dropout rates (Neilson et al., 2019). For 2020, the program was updated and aired as part of the 'Aprendo en casa' initiative, which provided lessons through multiple channels, including online platforms, television, and radio (MINEDU, 2020).

To evaluate the effects of this intervention, we conducted a randomized encouragement design that involved making phone calls to encourage families to watch the DFM episodes. The videos were aired for high-school students in two one-hour sessions on September 4 and 11, 2020. The sample consisted of families in schools with the highest dropout rates in urban areas, for which we had at least one parent's phone number for 9$^{\text{th}}$ and 10$^{\text{th}}$ grade students, totaling around 80,000 families from 1,978 schools. We randomly assigned 50% to the treatment group. Encouragement calls informed families about the video transmission, its value, and invited them to watch together. 64% of parents in the treatment group received the message, and 79.9% had access to the TV signal.

We obtained administrative data on student enrollment for 2021. To estimate the effects of the phone calls, we compared outcomes between students in the treatment and control groups to generate an intention-to-treat (ITT) estimate. Additionally, we examined whether the effects differed across individual and school characteristics to explore potential heterogeneity using traditional analysis and the

[1] However, there is a body of pre-COVID-19 literature examining the effects of television on educational outcomes, including, for instance, studies by Mares et al., 2015 and Watson and McIntyre, 2020, as well as research on the causal effects of Sesame Street on educational outcomes conducted by Kearney and Levine, 2019.

machine learning procedure by Chernozhukov et al. (2018). We also estimated treatment-on-the-treated (ToT) effects using a dummy for whether the encouragement message was fully delivered as a proxy for take-up.

Our analysis yields three main results. Firstly, the ITT estimates indicate a significant reduction in dropout rates for the treatment group, ranging from 0.59 to 0.69 percentage points, compared to the control group's average dropout rate of 10.2%. Secondly, heterogeneity analysis shows stronger effects for girls and students from high dropout and high poverty schools, confirmed by machine learning. Lastly, ToT estimates imply effects between 0.92 and 1.07 percentage points, with no indication that differences in take-up explain the heterogeneity in ITT effects.

The paper contributes to several research areas. Firstly, it reaffirms the cost-effectiveness of providing information to enhance educational outcomes (World Bank, 2023). In particular, it extends the literature by showing that television can be an efficient delivery method, and stressing the role of information provision in educational contexts experiencing severe shocks. Secondly, it adds to the literature on remote interventions during the Covid-19 pandemic (e.g., Angrist et al., 2022, 2023; Carlana and La Ferrara, 2024; Wang et al., 2023; Lichand and Christen, 2020). Lastly, it contributes to the literature on the causal impacts of delivering educational content through television in a remote setting (Kearney and Levine, 2019), presenting the effects of an innovative intervention evaluated using an encouragement design.

2 Background: Education in Peru and the DFM project

2.1 Education in Peru Before the Pandemic

Peru's educational system is managed by the Ministry of Education (MINEDU) and includes three levels: early childhood (ages 2-5), primary (ages 6-12), and secondary (ages 13-17), all free in public schools. By 2019, net enrollment rates were over 97.1% for primary and 87% for secondary education. Despite improvements, Peru still lags in learning outcomes and shows significant socioeconomic disparities. In the 2018 PISA report, Peruvian students ranked 64th out of 77 countries in mathematics, reading, and science at age 15. Peru has one of the largest performance gaps between low- and high-income students and the highest variance in PISA test outcomes due to socioeconomic conditions (Bos et al. (2016), OECD (2019)). Similarly, national evaluations show about a one standard deviation difference between children in the richest and poorest quintiles (Berlinski and Schady (2015)).

Ensuring students complete education up to secondary level is an important challenge. Before the pandemic, 8.1% of children dropped out by age 13, and 13.2% did not complete secondary education in 2019. Appendix Figure A1 shows dropout rates by grade and gender for 2018-2019, indicating critical points for dropout from the end of primary and throughout secondary school, often due to transition costs and opportunity costs of attending school. Boys generally had higher dropout rates than girls. School attendance and dropout rates are closely linked to child labor (Gunnarsson et al. (2006)).

2.2 The "Decidiendo para un Futuro Mejor" (DFM) project

The "Decidiendo para un Futuro Mejor" (DFM) project, developed in 2015 and 2016 by this research team (see Neilson et al. (2019) for details), aimed to improve education quality and reduce dropout rates by providing persuasive videos on the benefits of education, including information on wages and financial aid. The program, created jointly with the Ministry of Education (MINEDU), featured a four-episode telenovela with relatable plots and easy-to-understand infographics based on real survey data.

The episodes covered:

1. E1: "Learning the value of education" - The introductory episode presented the main characters and the choices they faced, along with highlighting the non-monetary returns of education.
2. E2: "Studying to live a better life" - The characters delved into the monetary benefits of completing high school and pursuing higher education, with gender-specific data presented in the infographic.
3. E3: "A scholarship for my dreams" - The characters discovered the financial challenges associated with higher education, but also learned about the availability of scholarships, credits, and work-study options. The infographic discussed the obstacles, the scale of financing mechanisms, and focused on the scholarship program in Peru, specifically Beca 18.
4. E4: "Choosing my major, a major decision" - The main characters confronted different higher education options aligned with their interests. The infographics presented information on the returns of various fields of study and emphasized the important skills associated with each.

Information was derived from Peru's National Households Survey (ENAHO) and included average salaries and gender-specific data. The program targeted students from 5th grade in primary school to 5th grade in high school. MINEDU and the research team, along with a screenwriter, developed a plot featuring characters Quique and Claudia, who faced socioeconomic challenges but aspired to complete high school and pursue further education. Quique aimed to convince his family of education's long-term benefits, while Claudia explored financing options for higher education. Claudia's younger brother, Diego, illustrated the importance of dedication to academic studies. Claudia opts for a university degree, while Quique decides on a technical path. Meanwhile, Claudia's younger brother, Diego, embodies an innocent optimism about his own educational plans. His storyline illustrates the importance of present-day effort and dedication to academic studies in realizing his optimistic educational and career goals.Thus, Diego's character serves as a secondary character within the intervention, contributing to its credibility and effectiveness by providing relatable perspectives for the intended audience.

Initially, the program was implemented through RCTs in both urban and rural schools, involving personal delivery of the videos in classroom settings. Teachers facilitated the presentation of the videos and post-episode discussions. Additional treatments included an app-based intervention and a focus on parents. These RCTs covered diverse samples. A formal evaluation by Neilson et al. (2019) showed a significant decrease in dropout rates after one and two years. In 2018, MINEDU further scaled up the program, incorporating it into the official curriculum for full-day schools. Recently, World Bank, 2023 highlighted DFM as a cost-effective information provision intervention.

2.3 Peru and the Pandemic

Peru faced severe impacts from COVID-19, with one of the highest rates of excess mortality in 2020-2021, at 528.6 per 100,000 people (Knutson et al. (2022)). The pandemic led to an 11% drop in GDP in 2020, increasing poverty from 20.2% in 2019 to 30.1% (World Bank (2021)). About 6.7 million jobs were lost during the peak of the pandemic (World Bank (2021)), exacerbated by the informality of the labor market (55.7% of non-agricultural jobs in 2020).

Schools in Peru experienced 34 weeks of full closure and 43 weeks of partial opening during the Covid-19 period (UNESCO). Although there are no specific estimates of learning loss in Peru, using the estimates in Patrinos (2023) for the impact of school closures, it could result in a decrease in learning equivalent to at least 0.34 standard deviations or approximately 1.25 years of schooling (based solely on the number of weeks of full school closures).

The Ministry of Education (MINEDU) created "Aprendo en casa" (AeC) to provide lessons through multiple channels considering internet access, language, and age differences. It included an online platform, national television broadcasts, and radio transmissions in various languages. TV schedules and radio broadcasts were announced weekly (MINEDU). The program allocated one hour of TV time and 30 minutes of radio time per day (Contraloría General de la República del Perú (2021)).

3 Research Design and Methods

In this section we describe the intervention and data sources. We also assess the balance in covariates in the baseline. Finally, we describe the methods used to estimate the impact of the program.

3.1 Research Design

Based on initial results from the DFM program, MINEDU updated the infographics and broadcasted the same soap-opera styled video during the AeC program. Episodes 1 and 2 were aired on September 4, 2020, and episodes 3 and 4 on September 11, 2020, making the broadcast available to the entire population.

Our study employed an *encouragement design*. Treated families received a short phone call informing them about the broadcast schedule, emphasizing the videos' value, and inviting them to watch together with their children. The sample comprised students from 1,978 urban schools with high dropout rates, focusing on 9th and 10th graders with at least one registered parental phone number. Parents from 989 schools were randomly assigned to treatment or control groups, stratified by three catgeories of school size[2].

The treatment group included 39,327 students' parents. Of these, 28,497 parents (72.5%) took the call, and 25,295 parents (88.8%) agreed to receive the full message, representing 64.3% of all households in the treatment group. Calls were made from September 1 to September 4, 2020, with 96.1% receiving the call before the first video broadcast. The median call duration was 3.5 minutes.

[2]Small (20 or fewer students in 9th and 10th grades), Medium (bewteen 21 and 50 students), and Large schools (more than 50 students).

3.2 Data

The main outcome and some of the covariates considered in the balance and subsequent estimations come from administrative records of student enrollment in the educational system for the years 2020 and 2021. Additionally, information about each school, including their poverty levels, number of teachers, and other relevant details, was also used. Take-up information was recorded through short surveys completed by each intervened parent. Furthermore, for each treatment and control student and parent, an array of educational and socioeconomic data was obtained from administrative records. Finally, socioeconomic data for each district in the sample was sourced from the 2020 ENAHO survey (*Encuesta Nacional de Hogares*).

3.3 Balance

As in any randomization, we now check balance in multiple dimensions. We check this at two levels. First, we study balance at the school level for two reasons: (i) we have access to many more variables at this level, and (ii) the randomization to be selected in the treatment group was implemented at the school level. Second, we study balance at the student level for a few variables for which we collected data after the treatment was implemented. Table 1 presents balance on observables at the school level in Panel A (including variables that capture the characteristics of the municipalities where the schools are located) and at the individual level In Panel B. We find balance on most variables with three exceptions: the share of rural schools in the area where the school is located, and student gender and age. However notice the the size of the differences does not seem economically relevant. For example, the share of girls is 47.6% versus 49.2%, and years of schooling of the parent is 8.77 versus 8.66. These are not relevant differences. The statistical significance is probably an artifact of the fact that our sample is really big: we have more than 80,000 individual observations.

All in all, our reading of these results is that there are no economically relevant differences between the treatment and control groups in most of the relevant variables. Still, we will control for the unbalanced variables in our main estimates (results are robust to these controls).

3.4 Statistical Methods

The random assignment of the encouragement treatment allows us to estimate the treatment effect by comparing average outcomes for the treatment and control groups. To increase precision and control for imbalances, we follow Duflo et al. (2008) and use a regression specification that includes various student and school characteristics. The direct impact of the program (the ITT estimator) is estimated using the following OLS regression:

$$Dropout_{is} = \alpha + \beta T_{is} + \Gamma \mathbf{X}_{is} + \epsilon_{is} \tag{1}$$

where $Dropout_{is}$ is a dummy for student i in school s not being enrolled by the end of 2021. T_{is} indicates if the student was in the encouragement treatment group; β captures the ITT effect. $\mathbf{X}_{is}$ includes covariates like strata fixed effects, school characteristics, and student characteristics. ϵ_{is} is the error term.

TABLE 1: Sample Balance on School-level and Student-level Observables

	Controls	Treated	Difference	Std. Error
Panel A: School-level Observables				
% with disability	0.013	0.013	0.000	0.001
% Female	0.477	0.483	0.006	0.005
Years of age	15.518	15.533	0.014	0.015
% Morning class	0.659	0.641	-0.018	0.019
% Afternoon class	0.128	0.151	0.022	0.015
N° Eligible	40.165	39.867	-0.298	1.075
Income quintile	3.267	3.279	0.012	0.060
Median income	6442.556	6599.964	152.540	126.950
% Rural area	0.028	0.017	-0.011*	0.007
N° Students	286.922	285.107	-1.815	7.129
N° Teachers	19.942	19.658	-0.284	0.452
N° Female	135.532	137.869	2.337	4.023
$t-1$ Dropout rate	0.092	0.091	-0.001	0.002
% TV ownership	0.190	0.193	0.003	0.007
% Internet connection	0.202	0.208	0.006	0.007
% Cellphone ownership	0.636	0.633	-0.002	0.007
% Female parent	0.669	0.670	0.001	0.008
% Parents no school	0.045	0.043	-0.002	0.002
% Parents prim. school	0.436	0.445	0.009	0.010
% Parents high school	0.416	0.412	-0.004	0.009
% Parents college	0.102	0.098	-0.004	0.004
Panel B: Student-level Observables				
Grade in 2020	9.496	9.499	0.003	0.004
Has disability	0.009	0.010	0.000	0.001
Female	0.476	0.492	0.016***	0.003
Juntos beneficiary	0.186	0.183	-0.003	0.003
Parents schooling years	8.765	8.660	-0.103***	0.026
Age (in years)	15.358	15.366	0.007	0.007

Notes: The average difference between groups comes from regressing each variable on treatment status, controlling for strata fixed effects. Robust standard errors. % Female is the share of female students; similarly for % Handicapped, % Morning Class, and % Afternoon Class. Income Quintile is the school's median income quintile; Median Income is the municipality's median income. % TV Ownership, % Internet Connection, and % Cellphone Ownership are the rates of households owning cable TV, having internet, and owning cellphones in the municipality. % Rural Area is the share of rural schools. $t-1$ Dropout is the 2019 dropout rate. N° Eligible is the number of 9^{th} and 10^{th} grade students; N° Students is the total number of students; N° Female is the total number of female students. Gender and disability are dummies indicating whether a student is female or has a disability. *Juntos* is a dummy for program beneficiaries. Parent's schooling years is the number of schooling years of the registered parent. Age is the student's age. * $p<0.1$, ** $p<0.05$, and *** $p<0.01$.

Even though the treatment was allocated at the individual level, we present estimates clustered at the *classroom* level to be conservative in our preferred specifications.

We also present heterogeneous treatment effects using both traditional regression analyses and a machine learning procedure suggested by Chernozhukov et al. (2018). Additionally, we estimate ToT models using an instrumental variable regression to understand the effects of actually receiving the message and whether the heterogeneous effects are related to differences in take-up rates. We use a dummy indicating whether the parent received the complete encouragement design message as the endogenous variable and instrument it using the intention-to-treat dummy T_i.

4 Results

In this section, we present the primary results of our study on treatment effects. We begin by reporting ITT estimates. Next, we present heterogeneous ITT effects considering key dimensions related to the potential effects of the treatment. Finally, we present TOT estimates.

4.1 Intention to Treat Estimates

Table 2 presents the ITT estimates of an initial set of specifications. The first column consists of the most naive specification, considering only strata fixed effects and robust standard errors, finding an ITT effect of -0.59 percentage points (pp), significant at the 1% level. This compares with an average dropout rate of 10.2% in the control group and with an average dropout rate of 7.85% in 2019. These relatively high baseline dropout rates are due to the fact that the sample where we implemented our experiment consists of schools in the two highest quintiles of dropout rates. The second column presents the same estimates but with clustered standard errors at the classroom level. While this is not necessary, as the treatment was allocated at the individual level, we do so in all the following specifications to be conservative. Unsurprisingly, the standard errors increase and now the effect is only significant at the 10% level.

Next, column (3) presents the ITT estimates adding a vector of individual-level control variables to improve the precision of our estimates and account for potential effects of the imbalances identified in Table 1. The variables are: a dummy variable indicating the student's grade level in 2020, a dummy variable indicating whether the student has any disabilities, a dummy variable indicating the student's gender, a dummy variable indicating whether the student is a beneficiary of the Juntos program[3], a variable indicating the number of years of schooling of the student's parent, and a variable indicating the student's age. The size of the ITT estimate increases to -0.63 pp, significant at the 10% level.

Next, column (4) adds school-level controls including dummies indicating the poverty quintile of the school in 2018, the dropout rate of the school in 2019, the total number of students in the school, the total number of teachers in the school, the total number of female students in the school, and the number of 9^{th} or 10^{th} graders. Again, the size of the ITT estimate slightly increases to -0.69 pp, significant at the 5% level. Finally, column (5) adds district-level fixed effects to account for any variability across districts. The ITT estimate increases in size to -0.87 pp, significant at the 5% level.

[3]Juntos is a national conditional cash transfer program in Peru. See World Bank (2019) for details.

TABLE 2: ITT Effects on Dropouts on 2021

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment Dummy	-0.0059***	-0.0059*	-0.0063*	-0.0069**	-0.0085*	-0.0009
	(0.0021)	(0.0036)	(0.0035)	(0.0035)	(0.0044)	(0.0101)
Clustered Standard errors		Classroom	Classroom	Classroom	Classroom	Classroom
Student Controls			X	X	X	X
School Controls				X	X	X
District FE					X	
Sample	Complete	Complete	Complete	Complete	Complete	Last-day calls
Observations	81,654	81,654	81,329	81,329	81,329	43,140

Notes: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$. Standard errors in parentheses. Column (1) uses only randomization strata as controls and robust standard errors. Column (2) replicates (1) but clusters standard errors at the classroom level. Column (3) adds student covariates: grade fixed effects, disability, gender, parent's schooling years, Juntos beneficiary, and age. Column (4) adds school-level covariates: number of eligible students, past school dropout rate, school poverty quintile, total students, teachers, and female students. Column (5) adds district fixed effects. Column (6) estimates effects on students whose parents received the encouragement call on September 4, using 43,140 observations: 993 in the restricted treatment group and 42,320 in the control group. The control mean outcome is 0.102 in all specifications.

The evidence so far indicates that the encouragement design had a significant negative impact on dropout rates, suggesting that the information provided in the videos is relevant and confirming previous results of the DFM in Peru. However, the actual call to encourage watching the video may have directly affected dropout. To test this, we restricted the sample to families who received the encouragement "late" (on September 4, the same day the first video was broadcast). Results show a much smaller effect for this group (-0.14 pp), suggesting that the direct effect of the call is not driving the results. While this exercise is not perfect because the date of the call is not random and because families could still watch the second video, it is still suggestive evidence that the direct effect of the call is not what is driving the results.

Overall, the ITT estimates imply a decrease of about 0.6 percentage points (p.p.) in dropout rates from an average dropout rate of 10.2% in the control group. These effects are about one third of the original in-person implementation of the DFM program (Neilson et al. (2019)) and smaller than the effects reported in J-PAL (2019) for interventions affecting perceived returns and motivation of students. The average (median) of the estimated impacts is approximately 4.2 p.p. (3.2 p.p.). This is expected given the nature of the intervention we studied, which relies on remote delivery via television rather than direct in-person engagement, but it still suggests that even modest interventions can have a meaningful effect on dropout rates.

4.2 Heterogeneous Treatment Effects

Having shown the average effect of the intervention on dropout probability, we now explore heterogeneous treatment effects to understand the underlying mechanisms. We present both traditional analyses and use the machine learning procedure by Chernozhukov et al. (2018).

We consider heterogeneity on the following dimensions:

- Gender: Examining different effects for male and female students (as both populations may have different probabilities of dropping out as documented in previous research, see the review in J-PAL (2019)).
- Grade Level: Assessing if impacts vary by grade level, as dropout rates increase in higher grades (Appendix Figure A1).
- Participation in the Juntos Program: Using Juntos beneficiary status as a proxy for poverty.
- Educational Level of Parents: Considering if parent's education (above/below median) affects outcomes.
- School Poverty Levels: Comparing schools below/above the third quintile of poverty in 2018.
- School's Dropout Rate: Analyzing schools with dropout rates below/above the median in 2019.

Using Chernozhukov et al. (2018)'s method, we estimate heterogeneous treatment effects by generating "proxy predictors" for the conditional average treatment effect (CATE). We include all covariates in $\mathbf{X}_{is}$. The Best Linear Predictor (BLP) of the CATE, average treatment effects (ATE), and heterogeneity loading (HET) parameters are estimated. Table 3 shows results for elastic net (EL) and random forest (RF). The ATEs align with previous ITT models, and HET coefficients are significantly different from zero, indicating substantial heterogeneity.

Students from lower poverty and lower dropout schools benefit more. The least affected group has lower proportions of students from high poverty schools (0.287 in EL and 0.277 in RF) compared to the most affected group (0.419 in EL and 0.416 in RF), and lower proportions from high dropout schools (0.470 in EL and 0.480 in RF) compared to the most affected group (0.546 in EL and 0.558 in RF). Gender differences show female students benefit more, as evidenced by the lower proportion of girls in the least affected group (0.448 in EL and 0.419 in RF) compared to the most affected group (0.495 in EL and 0.479 in RF). Differences in grade, Juntos status, and parents' education are not significant.

These results motivate the estimation of traditional heterogeneity analysis (i.e., estimating treatment effects for subsamples). Traditional heterogeneity analyses (Panel A of Figure 1 and Appendix Table 1) confirm that the most relevant heterogeneity comes from school-level variables: poverty and pre-COVID dropout rates. The estimate for students in high-poverty and high-dropout schools is -2.18 and -1.26 percentage points (pp), respectively, while estimates for lower poverty/dropout groups are near zero. Effects for girls are -0.92 pp (significant) and for boys are -0.49 pp.

4.3 Treatment on Treated Effects

We now estimate ToT models to (i) provide estimates of the call's effect on outcomes using the encouragement design as an instrumental variable, and (ii) understand if ITT effect differences can be explained by take-up differences. Our measure of take-up is a dummy for whether a parent received the complete treatment call. Table 4 presents ToT estimates (Panel A) and first stage results (Panel B). The effects of treatment status on take-up are around 0.64 across all columns, implying controls cannot explain take-up differences. ToT estimates range between -0.91 and -1.06, similar to the statistical significance in Table

TABLE 3: Heterogeneous Treatment Effects Estimates using Machine Learning

PANEL A: Best linear prediction (BLP): coefficient of average and heterogeneous treatment effects

	Elastic Net			Random Forest	
	ATE	HET		ATE	HET
Dropout	-0.011**	0.961***		-0.008**	0.786***
	(-0.018,-0.005)	(0.898,1.023)		(-0.015,-0.002)	(0.713,0.857)
	[0.001]	[0.000]		[0.028]	[0.000]

PANEL B: Classification Analysis (CLAN), difference in variables between most and least affected groups

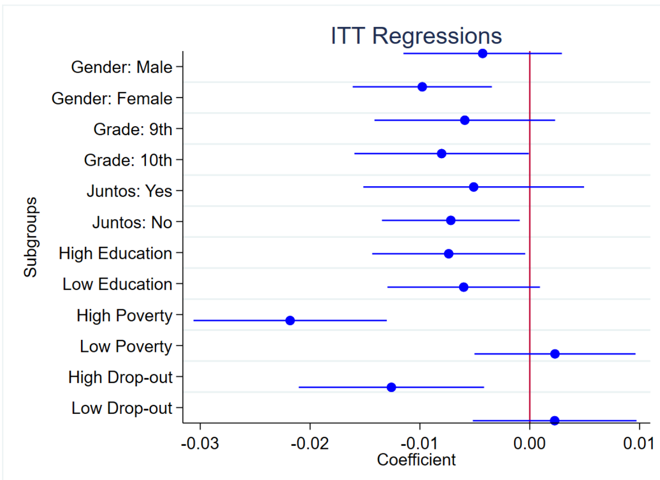
	Elastic Net			Random Forest		
	Least Affected	Most Affected	Difference	Least Affected	Most Affected	Difference
Gender	0.448	0.495	-0.046***	0.419	0.479	-0.059***
	(0.438,0.459)	(0.484,0.506)	(-0.062,-0.031)	(0.408,0.430)	(0.468,0.489)	(-0.075,-0.044)
	-	-	[0.000]	-	-	[0.000]
Grade in 2020	12.500	12.500	0.000	12.490	12.500	-0.005
	(12.490,12.510)	(12.490,12.510)	(-0.015,0.015)	(12.480,12.500)	(12.480,12.510)	(-0.020,0.011)
	-	-	[1.000]	-	-	[1.000]
Juntos beneficiary	0.167	0.170	-0.004	0.154	0.158	-0.004
	(0.158,0.175)	(0.162,0.178)	(-0.015,0.007)	(0.146,0.162)	(0.150,0.166)	(-0.015,0.007)
	-	-	[0.976]	-	-	[1.000]
High education	0.489	0.490	0.004	0.451	0.460	-0.006
	(0.478,0.500)	(0.479,0.500)	(-0.011,0.020)	(0.440,0.462)	(0.449,0.471)	(-0.021,0.009)
	-	-	[1.000]	-	-	[0.887]
High poverty	0.287	0.419	-0.133***	0.277	0.416	-0.138***
	(0.276,0.297)	(0.409,0.429)	(-0.148,-0.119)	(0.267,0.287)	(0.406,0.426)	(-0.152,-0.123)
	-	-	[0.000]	-	-	[0.000]
High drop-out	0.470	0.546	-0.079***	0.480	0.558	-0.074***
	(0.459,0.480)	(0.535,0.557)	(-0.094,-0.064)	(0.470,0.491)	(0.547,0.569)	(-0.089,-0.059)
	-	-	[0.000]	-	-	[0.000]

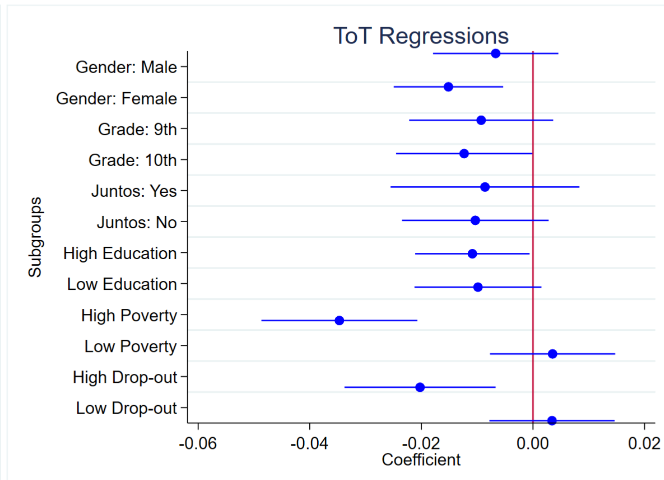
Notes: Panels A and B present the medians over 100 random sample splits for each parameter and predictive model, with the p-values for the null hypothesis (parameter equal to zero) shown in brackets. For more details about the methodology employed, see Chernozhukov et al. (2018). Standard errors clustered at the classroom level are in parentheses. * for $p < 0.1$, ** for $p < 0.05$, and *** for $p < 0.01$.

FIGURE 1: Heterogeneity Analysis

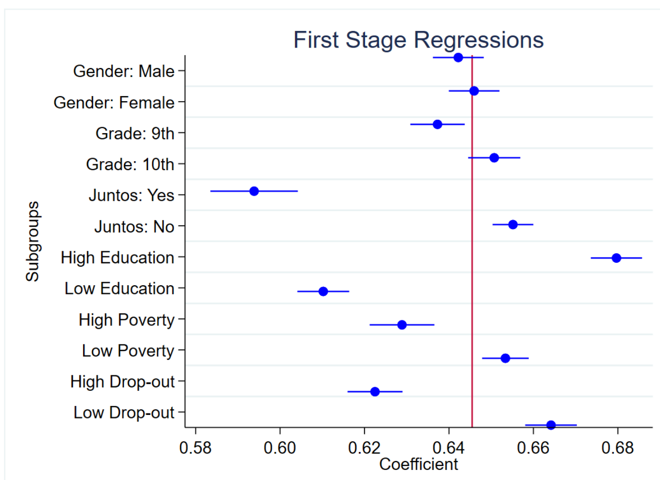
Panel A

Panel B





Panel C



Notes: Dots indicate point estimates and lines around them show 90% confidence intervals. Standard errors are clustered at the classroom level. Panel A presents ITT effects (Panel A of Appendix Table 1), Panel B presents ToT effects (Panel B of Appendix Table 1), and Panel C presents first stages (ie., the effect of treatment assignment on take-up) (Panel A of Appendix Table 1). All specifications as in column (4) of Table 2. High and Low values are defined using sample splits above and below the median value of each covariate.

2. Adding district effects in column (5) increases the ToT effect to -1.34.[4] Heterogeneity effects in Panels B and C of 1 (and Appendix Table 1) suggest take-up differences do not explain ITT effect heterogeneity. In summary, ToT estimates confirm significant treatment effects with similar heterogeneity results.

TABLE 4: ToT Effects on School Drop-out

	(1)	(2)	(3)	(4)	(5)
	PANEL A: ToT Estimates				
Treatment Dummy	-0.0091***	-0.0091*	-0.0098*	-0.0107**	-0.0134*
	(0.0033)	(0.0055)	(0.0054)	(0.0054)	(0.0069)
	PANEL B: First-stage take-up estimates				
Treatment Take-up	0.6430***	0.6430***	0.6442***	0.6440***	0.6380***
	(0.0024)	(0.0028)	(0.0027)	(0.0027)	(0.0034)
Clustered Standard errors		Classroom	Classroom	Classroom	Classroom
Student Controls			X	X	X
School Controls				X	X
District FE					X
Observations	81,654	81,654	81,329	81,329	81,320

Notes: See Table 2.

5 Conclusions

The COVID-19 pandemic has disrupted educational systems worldwide, increasing challenges like school dropout rates. This paper investigates the impact of the "Decidiendo para un Futuro Mejor" (DFM) informational campaign on high-school dropout rates in Peru. The intervention aimed to highlight the benefits of education and provide information on wages and financial aid.

Our ITT estimates indicate a reduction in dropout rates by approximately -0.6 percentage points (pp). This aligns with previous research on the DFM program. Heterogeneity analyses, using both machine learning and traditional methods, reveal that students from schools with higher poverty and dropout rates benefit more. Female students also responded more positively than male students. ToT models show that differences in take-up rates do not explain the observed heterogeneity in ITT effects.

Our findings highlight the potential of informational interventions to reduce dropout rates. The significant effects and heterogeneous treatment effects suggest that targeted informational campaigns can be cost-effective. Further research could explore the long-term impacts of such interventions in different contexts.

This study contributes to the literature on educational interventions by demonstrating the effectiveness of informational campaigns in reducing school dropout rates. The results underline the potential of television for educational interventions, especially during crises like the COVID-19 pandemic. The DFM program, integrated into the national "Aprendo en casa" initiative, showcases how television can deliver

[4]In practice, ToT estimates are Wald estimators Angrist and Keueger (1991); Wald (1940), re-scaling ITT estimates by the dummy indicating treatment status in the first stage, about 0.64.

critical educational content and support remotely. We hope these insights will inform policymakers and practitioners in designing effective educational programs that leverage information to improve student outcomes.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to copy-edit the text of the paper. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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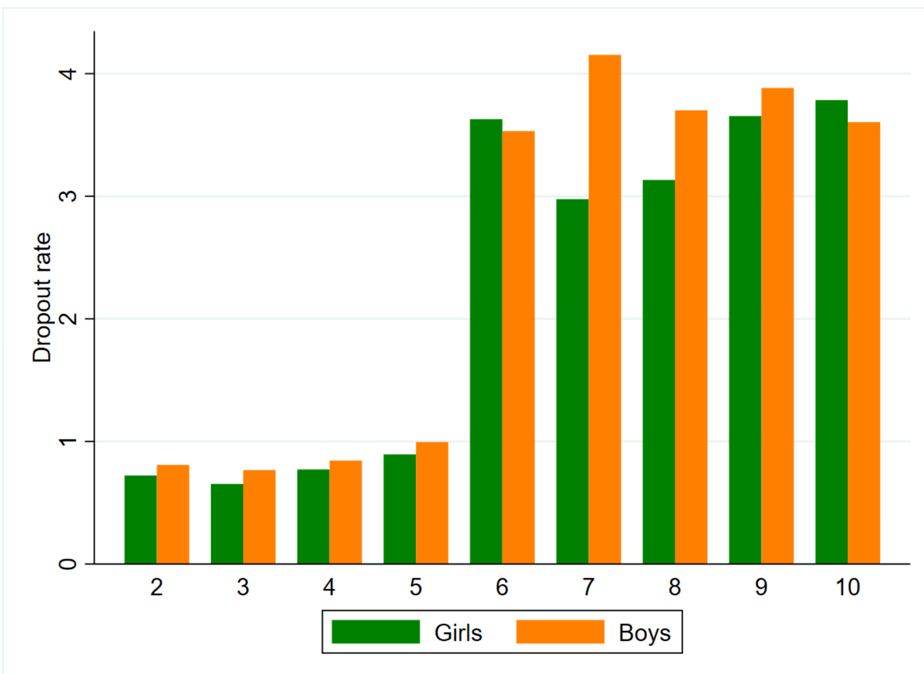
Appendix Table 1: Heterogeneous Effects

	Female	9^{th} grade	Juntos	Parent's Schooling	Poverty	Drop-out
	Panel A: Heterogeneity Analyses					
Yes/High	-0.0098**	-0.0059	-0.0051	-0.0074*	-0.0218***	-0.0126**
	(0.0039)	(0.0050)	(0.0061)	(0.0042)	(0.0053)	(0.0051)
No/Low	-0.0043	-0.0080*	-0.0072*	-0.0060	0.0023	0.0023
	(0.0044)	(0.0048)	(0.0038)	(0.0042)	(0.0045)	(0.0045)
	Panel B: ToT Estimates					
Yes/High	-0.0151**	-0.0093	-0.0086	-0.0109*	-0.0347***	-0.0202**
	(0.0060)	(0.0078)	(0.0103)	(0.0062)	(0.0085)	(0.0082)
No/Low	-0.0067	-0.0123*	-0.0103	-0.0099	0.0035	0.0034
	(0.0068)	(0.0074)	(0.0080)	(0.0069)	(0.0068)	(0.0068)
	Panel C: First-stage estimates					
Yes/High	0.6460***	0.6373***	0.5939***	0.6797***	0.6289***	0.6225***
	(0.0036)	(0.0039)	(0.0063)	(0.0037)	(0.0047)	(0.0040)
No/Low	0.6422***	0.6507***	0.6552***	0.6102***	0.6534***	0.6642***
	(0.0037)	(0.0038)	(0.0029)	(0.0037)	(0.0034)	(0.0037)

Notes: Panel A presents ITT effects, Panel B presents ToT effects, and Panel C presents first stages (ie., the effect of treatment assignment on take-up). High and Low values are defined using sample splits above and below the median value of each covariate. All the specifications include the same set of covariates as in column (4) in Table 2, i.e. including , randomization strata, student characteristics (grade fixed effects (9th and 10th grade), a disability dummy, a gender dummy, dummies for parent's schooling years, dummies for beneficiaries of the Juntos social program, and dummies for age), school characteristics (number of students eligible for treatment (i.e., 9th and 10th grade students), past school dropout rate, school poverty quintile fixed effects, total number of students enrolled, number of teachers, and the number of female students enrolled). Standard errors clustered at the classroom level are in parentheses. * for $p < 0.1$, ** for $p < 0.05$, and *** for $p < 0.01$.

FIGURE A1: 2018-2019 Interannual dropout rate



Notes: SIAGIE enrollment data for 2018 and 2019, only students enrolled in primary or secondary education levels were considered.