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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 about the future benefits of schooling 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* uses videos to highlight the advantages of education while providing concrete information on wages and financial aid opportunities for higher education. We evaluate the impact of this intervention on dropout rates in 2021 using a randomized encouragement design with a sample of over 80,000 families with high school students. The intervention involved phone calls to promote watching television during the broadcast of *DFM* videos. Our findings indicate that the encouragement led to a significant reduction in school dropout rates, with intention-to-treat effects of approximately -0.6 percentage points, which is substantial given the average dropout rate of 10.2% in the control group. The effects are stronger for students from schools with higher baseline dropout and poverty rates. Additionally, we find larger effects for girls, with no observable differences based on parental education levels. Suggestive evidence indicates that the observed effects are not primarily driven by the direct impact of the phone calls but rather by the encouragement to watch DFM. These results highlight the potential of cost-effective strategies to mitigate the adverse effects of major negative shocks on educational trajectories.

JEL Codes: 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 (2023b)). 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 growing body of literature by assessing the effects of educational information provision during the challenging circumstances of the COVID-19 pandemic, representative of major adverse shocks that can negatively affect educational trajectories.

The COVID-19 pandemic, with its substantial economic and social consequences and widespread school closures, heightened the risk of children dropping out and experiencing learning losses UNICEF, 2021. In response, various remote interventions were implemented, including mentoring and tutoring Angrist et al., 2022, 2023; Carlana and La Ferrara, 2024; Hassan et al., 2024, audio messages Wang et al., 2023, and text messages Lichand and Christen, 2020. Many countries also relied on television to deliver educational content during the crisis ITU, 2020; UNICEF, 2020.[1]

The main premise of this paper is that the provision of information may be particularly relevant in the context of significant adverse shocks, such as COVID-19 and, more generally, during epidemics and pandemics, natural disasters, or social conflicts that disrupt the functioning of school systems. These are periods when both the direct and opportunity costs of attending school, as well as the salience of these costs, likely increase relative to the perceived future benefits of remaining in school. Several papers study the causal effects of adverse shocks on school attendance and other variables related to human capital accumulation.[2] Similarly, several papers demonstrate that the salience of costs increases during periods when these costs have a more pronounced effect on welfare.[3] Thus, the context of COVID-19 serves as a case study for understanding the impacts of information-based interventions, both in terms of content and delivery, during periods of adverse shocks to educational outcomes.

This paper examines the impact of providing information about the benefits of education to families with high school children in Peru during the COVID-19 pandemic. The Ministry of Education in Peru (MINEDU) adapted the program titled *Decidiendo para un Futuro Mejor* (DFM) into a television format, which was broadcast nationally in 2020. DFM uses 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). The program was updated and aired as part of the 'Aprendo en casa' initiative in 2020,

[1] Notice that the effectiveness of television interventions remains unclear. However, there is a body of pre-COVID-19 literature examining the effects of television on educational outcomes, including studies such as Mares et al., 2015 and Watson and McIntyre, 2020, as well as research on the causal effects of *Sesame Street* on educational outcomes by Kearney and Levine, 2019.

[2] See, for instance, Jacoby and Skoufias, 1997 for conceptual arguments and Bandiera et al., 2024 for an application to the case of girls during the Ebola crisis in Sierra Leone from 2014 to 2016.

[3] For example, see Bordalo et al., 2022 for a conceptual rationale and Singhal, 2024 for evidence related to energy costs.

which provided lessons through multiple channels, including online platforms, television, and radio (MINEDU, 2020).

To evaluate the effects of the implementation of the DFM pogram in 2020, we use data from a randomized encouragement design implemented by MINEDU 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 there was at least one parent's phone number for 9th and 10th grade students, totaling around 80,000 families from 1,978 schools. The ministry randomly assigned 50% to the treatment group. Encouragement calls were implemented by MINEDU staff and informed families about the video transmission, its value, and invited them to watch together. A total of 79.9% of parents contacted had access to the TV signal, while the remaining 20.1%, who did not have access to TV, received a general message aimed at motivating them about the value of education for their children's future. Overall, 52% of parents in the treatment group received the message encouraging them to watch *DFM* on TV.

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. Furthermore, we examined whether the effects differed by individual and school characteristics to explore potential heterogeneity using traditional analysis and the 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 four 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. Thirdly, we present suggestive evidence that the effects of treatment operated thorugh the DFM intervention and not through a direct effect of the message. Lastly, ToT estimates imply effects between 1.14 and 1.34 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, 2023b). 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; Hassan et al., 2024). Lastly, it contributes to the literature on the causal impacts of delivering educational content through television in a remote setting (e.g., Kearney and Levine, 2019), presenting the effects of an innovative intervention evaluated using an encouragement design and applied in a period of a negative shock to the educational system.

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, 2023b 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).[4] Although there are no specific estimates of learning loss in Peru, using the estimates from Patrinos (2023) on the impact of school closures, the learning loss could amount 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).[5]

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)).

[4]The index of school closures for Peru from Our World in Data shifted to level 3 on March 12, 2020 (the maximum level, requiring the closure of all levels in all schools). It remained at level 3 until November 18, 2020, when it moved to level 2 (requiring closures for some levels or categories). It then decreased to level 1 on March 28, 2022 (implying recommendations for closures or significant alterations to normal operations), and finally returned to level 0 in October 2022.

[5]In addition, World Bank (2023a) reports that the average student in Peru lost 1.7 learning-adjusted years of schooling during the pandemic.

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 broadcast the same soap-opera-style video during the *AeC* program. Episodes 1 and 2 were aired on September 4, 2020, while episodes 3 and 4 were broadcast on September 11, 2020, making the content accessible to the entire population. This implies that our intervention occurred during the final period of full school closures, which spanned from March 12, 2020, to November 18, 2020. It is important to note that schools were not fully reopened until October 2022, and there were still significant restrictions on normal school operations throughout 2021, as discussed above.

Our study employed an *encouragement design*. Treated families received a brief phone call. The main message of the call varied depending on whether families had access to the TV network broadcasting *AeC* (*TV Peru*). If they had access, the message emphasized the broadcast schedule.[6] For families without access to *TV Peru*, the caller provided a general message emphasizing the importance of education and the possibility of contacting the school.[7] We will exploit this (non-random) variation below to understand the potential mechanisms behind the effects of the call.

The sample comprised students from 1,978 urban schools with high dropout rates, focusing on 9$^{\text{th}}$ and 10$^{\text{th}}$ graders with at least one registered parental phone number. MINEDU randomly assigned parents from 989 schools to treatment or control groups in order to receive an *individual* call.[8]

The treatment group consisted of 39,327 students' parents. Of these, 28,497 parents (72.5%) answered 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 between September 1 and September 4, 2020, with 96.1% of calls completed before the first video broadcast. The message with invitation to watch the program was delivered to 79.8% of families, while the remaining 20.2% received the general message focused. The median call duration was 3.5 minutes, and the calls were made by MINEDU personnel. The cost per student of the encouragement design was $1.5 ($2.7 at PPP), including both personnel and call costs. The cost of updating the videos, adapting them to the *AeC* format, and airing them on open TV was

[6]The actual message was (our translation): "The reason for my call is to inform you that this and next Friday, *Aprendo en Casa* will have a special program about the importance of continuing to study, even in difficult situations like the ones we are facing. This special program will last one hour and will contain important information about the value of education in general, why it is important to pursue higher studies at an institute or university, and also about the financial support opportunities that exist to study in these centers. For students in 3$^{\text{rd}}$ and 4$^{\text{th}}$ year of secondary education, like **[Student_Name]**, the first part of this program will be broadcast this Friday, September 4, from 3 to 4 in the afternoon on TV Peru, and the second part next Friday, September 11, at the same time and channel. Don't miss the opportunity to watch this program with your family!"

[7]The actual message was (our translation): "The reason for my call is to remind you how important education is for achieving a better future and to offer a message of support during these difficult times. Despite the challenges, it is crucial that families support the children and young people in the household to continue with their studies and reach their goals. Remember that the tutor of **[Student_Name]** and the principal of their school are available to support you. If you have difficulties contacting them, you can also reach out to the **UGEL** to which **[Student_Name]**'s school belongs."

[8]The randomization was stratified by three categories of school size: small (20 or fewer students in 9$^{\text{th}}$ and 10$^{\text{th}}$ grades), medium (bewteen 21 and 50 students), and large schools (more than 50 students).

approximately \$52,000 (about \$93,500 at PPP). Therefore, the average cost per student, considering the two cohorts of students targeted by the intervention, was about \$0.05 (\$0.09 at PPP).

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 because we have access to many more variables at this 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

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^{o} Eligible is the number of 9^{th} and 10^{th} grade students; N^{o} Students is the total number of students; N^{o} 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 *** $p < 0.01$.

like strata fixed effects, school characteristics, and student characteristics. ϵ_{is} is the error term. Even though the treatment was allocated at the individual level and it was delivered in a period where the schools were closed, 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 treatment-on-the-treated (ToT) models using instrumental variable regression to assess the effects of actually receiving the encouragement to watch DFM through television and to examine whether the heterogeneous effects are related to differences in take-up rates. Specifically, we use a dummy variable indicating whether the parent received the encouragement design message to watch DFM 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 treatment effects. Next, we present heterogeneous ITT effects considering key dimensions related to the potential effects of the treatment.

4.1 Treatment Effects

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 implemented at the individual level and the schools were mostly closed during the relevant period, 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[9], 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

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

TABLE 2: ITT Effects on Dropouts in 2021

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment Dummy	-0.0059***	-0.0059*	-0.0063*	-0.0069**	-0.0085*	-0.0069**
	(0.0021)	(0.0036)	(0.0035)	(0.0035)	(0.0044)	(0.0035)
Clustered Standard errors		Classroom	Classroom	Classroom	Classroom	Classroom
Student Controls			X	X	X	X
School Controls				X	X	X
District FE					X	
Method	OLS	OLS	OLS	OLS	OLS	Double Lasso
Observations	81,654	81,654	81,329	81,329	81,329	81,329

Notes: * for $p < 0.1$, ** for $p < 0.05$, and *** for $p < 0.01$. Standard errors in parentheses. Column (1) presents the most basic specification with only randomization strata as control variables and robust standard errors. Column (2) replicates column (1) but uses clustered standard errors at the classroom level. Column (3) includes student characteristics as covariates: 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. Column (4) includes school-level covariates: 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. Column (5) adds fixed effects at the district level to the control set. Column (6) presents the results of a double-selection Lasso model where controls are selected endogenously. In all specifications, the control mean outcome is 0.102.

of 9$^{\text{th}}$ or 10$^{\text{th}}$ graders. Again, the absolute value of the ITT estimate slightly increases to -0.69 pp, significant at the 5% level. Next, column (5) adds district-level fixed effects to account for any variability across districts. The ITT estimate increases in size to -0.85 pp, significant at the 5% level. Finally, column (6) presents the ITT estimate using a double-selection Lasso model, where controls are selected endogenously. The size of the ITT estimate remains consistent with previous results, with a coefficient of -0.69 pp, significant at the 5% level.

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 may have directly affected dropout. Exercises in the Table 3 try do deal with this point studying different margins. In Column (1) 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 (-0.09 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. Next, Column (2) presents treatment effects on the families that received the "general message" without mention of the broadcasting of DFM in TV (because they did not have access to TV Peru). The effect is 0.30 p.p. and not different from 0. As before, while this is a perfect exercise, because the content of the message was not randomly allocated, it is very suggestive that the effects of the encouragement call o not work through direct effects of the message or a general motivation to increase the demand for education. Thus, it serves as a king of placebo test for the DFM videos. Finally, column (3) deals with an additional margin: effects on people that did not received the message but were part of treatment group (and therefore attended the same school of several treated students). This serves both as placebo and also to identify potential spillovers of the message. again, the treatment effects is 0. A simple explanation for the absence of spillover effects at the school level is that this was a period in which the schools were fully or at least partially closed, as previously discussed. In all, results in Table 3 suggest that the effects of the encouragement design operate basically through the actual watching of the videos in Peru TV.

TABLE 3: ITT Effects on Dropouts on 2021 by Message Details

	(1)	(2)	(3)
Treatment Dummy	-0.0009	0.0030	0.0062
	(0.0101)	(0.0040)	(0.0043)
Sample	Last Day Call	No TV Peru Message	No Message
Observations	43,140	61,203	56,124

Notes: * for $p < 0.1$, ** for $p < 0.05$, and *** for $p < 0.01$. Clustered standard errors at the class-room level in parentheses. All specifications include student- and school-level controls. Column (1) estimates treatment effects on the subset of students whose parents received the encouragement call on September 4. Column (2) estimates treatment effects for students whose parents received the general message (without mention of the broadcasting of DFM videos on TV Peru). Column (3) presents treatment effects for students whose parents did not receive any message but were in the treatment group. In all specifications, the control mean outcome is 0.102.

Overall, the ITT estimates suggest a decrease of approximately 0.6 percentage points (p.p.) in dropout rates from an average dropout rate of 10.2% in the control group. These effects are much smaller than those observed in the original in-person implementation of the DFM program (Neilson et al. (2019)) and are also smaller than the effects reported in J-PAL (2019) for interventions aimed at influencing perceived returns and motivation among students. The average (median) of the estimated impacts is approximately 4.2 p.p. (3.2 p.p.). This result is expected given the nature of the intervention studied, which relies on remote delivery via television rather than direct in-person engagement. Nonetheless, it underscores that even modest interventions can have a meaningful impact on dropout rates, particularly during periods when dropout rates may rise, as discussed in the introduction.

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 been affected differently by COVID and DFM as documented in previous research, see the review in J-PAL (2019) and Bandiera et al., 2024).
- 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 4 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.

TABLE 4: 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

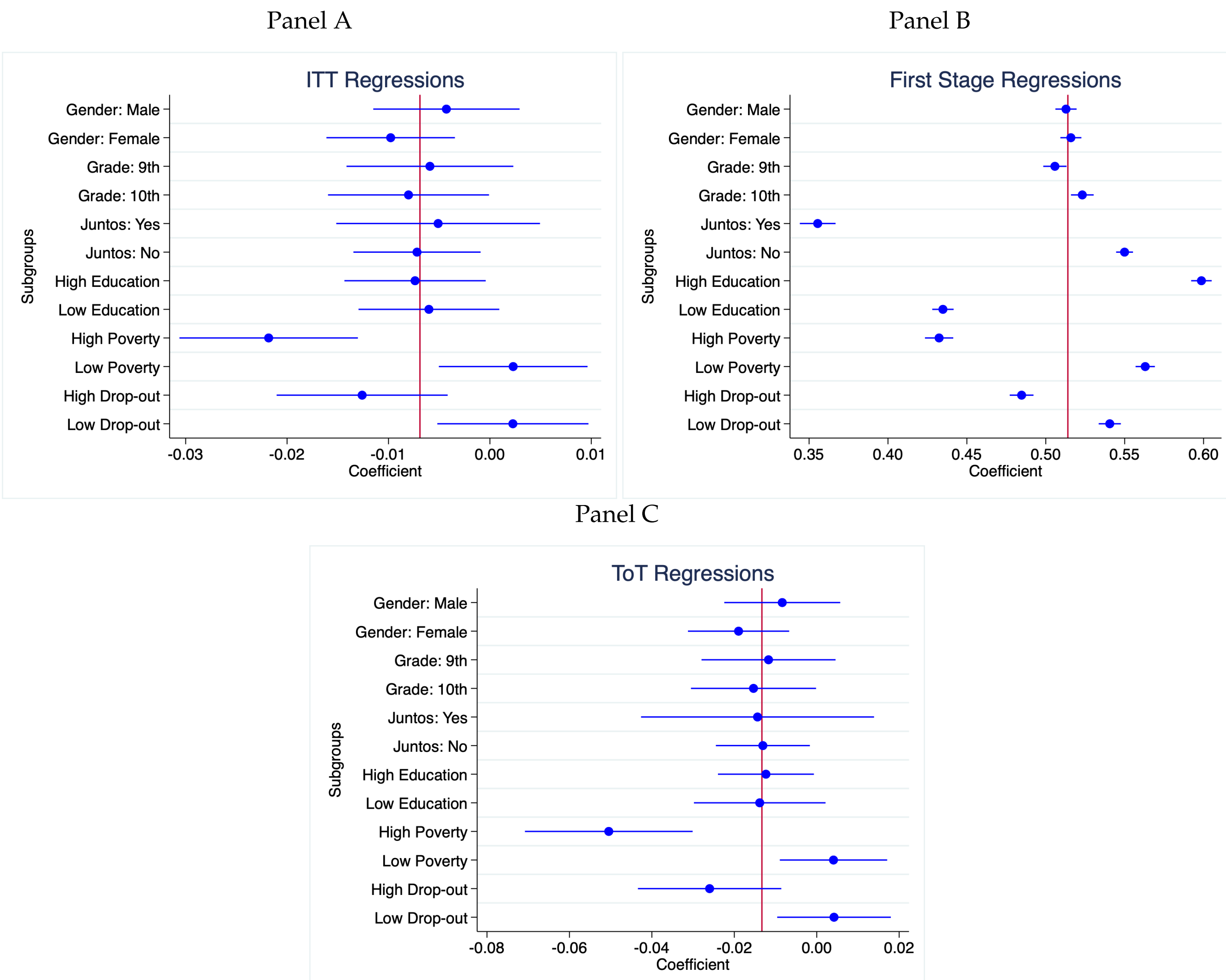
	Elastic Net			Random Forest		
	Least Affected	Most Affected	Difference	Least Affected	Most Affected	Difference
Gender	0.448	0.495	-0.046***	0.419	0.479	-0.059***
	(0.438,0.459)	(0.484,0.506)	(-0.062,-0.031)	(0.408,0.430)	(0.468,0.489)	(-0.075,-0.044)
	-	-	[0.000]	-	-	[0.000]
Grade in 2020	12.500	12.500	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 $p < 0.01$.

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 2) 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 -0.98 pp (significant) and for boys are -0.43 pp.

FIGURE 1: Heterogeneity Analysis



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 2), Panel B presents first stages (ie., the effect of treatment assignment on take-up) (Panel C of Appendix Table 2), and Panel C presents ToT effects (Panel B of Appendix Table 2). 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. The red vertical line marks the estimated effects for the complete sample as a benchmark.

Overall, these patterns contribute to understanding the mechanisms at play and provide insights into the external validity of this type of intervention. The program was implemented during a period of severe disruption to the educational system, within a sample characterized by high dropout rates. The results in this section suggest that populations in areas at greater risk of being affected by the shock experienced the most significant impacts. Specifically, students attending schools in high-poverty areas and those with a higher ex-ante share of school dropouts were the most affected. This may help explain the magnitude of the effects, as the intervention disproportionately benefits students who may need it the most. In contrast, the effects are close to zero for students in low-poverty areas and schools with lower ex-ante dropout risks. This suggests that interventions like the one studied in this paper could be targeted to specific populations that gain the most from such interventions. Interestingly, the absence of heterogeneous effects by family human capital implies that the effects cannot be primarily attributed to traditional mechanisms, such as parental responses to information provision on education. Instead, they appear more closely related to the risk of dropping out during the severe negative shock caused by COVID-19.[10] A similar argument applies to the larger effects observed for girls. While pre-COVID dropout rates were higher for boys than for girls, the estimated effects appear to be bigger for girls. This aligns with previous evidence suggesting that negative shocks like COVID-19 may disproportionately affect girls (eg., Bandiera et al., 2024).

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. Appendix Table 1 presents ToT estimates (Panel A) and first stage results (Panel B). The effects of treatment status on take-up are around 0.51-0.52 across all columns, implying controls cannot explain take-up differences. ToT estimates range between -1.14 and -1.34, similar to the statistical significance in Table 2. Adding district effects in column (5) increases the ToT effect to -1.635.[11] Heterogeneity effects in Panels B and C of 1 (and Appendix Table 2) suggest take-up differences do not explain ITT effect heterogeneity. In summary, ToT estimates confirm significant treatment effects with similar heterogeneity results that cannot be explained by heterogenous take-up rates.

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 negative impact aligns with previous research on the DFM program but while the effects are smaller, as expected, as this was a softer implementation of the program (by remotely using TV versus in-person; in the house versus in the school with a teacher acting as a mediator) at the same time the impacts are non-trivial suggesting that the effects of information interventions may be stronger in period of severe negative shocks, as

[10] There are non-trivial differences in years of schooling of parents between groups above and below the median: the median is 6 years of schooling for the group below the median and 11 years for the group above the median.

[11] 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 0.52.

COVID. Actually, 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 strongly 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, especially during emergency periods such as the COVID-19 pandemic. The significant effects and heterogeneous treatment effects suggest that targeted informational campaigns can be highly cost-effective. Further research could explore the long-term impacts of such interventions in different contexts and investigate the mechanisms underlying these effects. For instance, we lack information to determine whether the DFM intervention prompted additional investments by families and students that could be mechanisms to explain our results (e.g., engaging with other content available through the AeC program).

This study contributes to the literature on educational interventions by demonstrating the effectiveness of informational campaigns in reducing school dropout rates. The results highlight the potential of television as a medium for educational interventions, particularly during crises such as the COVID-19 pandemic. The DFM program, integrated into the national AeC initiative, exemplifies how television can deliver educational content and provide remote support, particularly to populations at higher risk.

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: ToT Effects on School Drop-out

	(1)	(2)	(3)	(4)	(5)
			PANEL A: ToT Estimates		
Treatment Dummy	-0.0114***	-0.0114*	-0.0123*	-0.0134**	-0.0163*
	(0.0041)	(0.0069)	(0.0068)	(0.0068)	(0.0084)
			PANEL B: First-stage take-up estimates		
Treatment Take-up	0.5135***	0.5135***	0.5151***	0.5144***	0.5223***
	(0.0025)	(0.0033)	(0.0032)	(0.0031)	(0.0039)
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

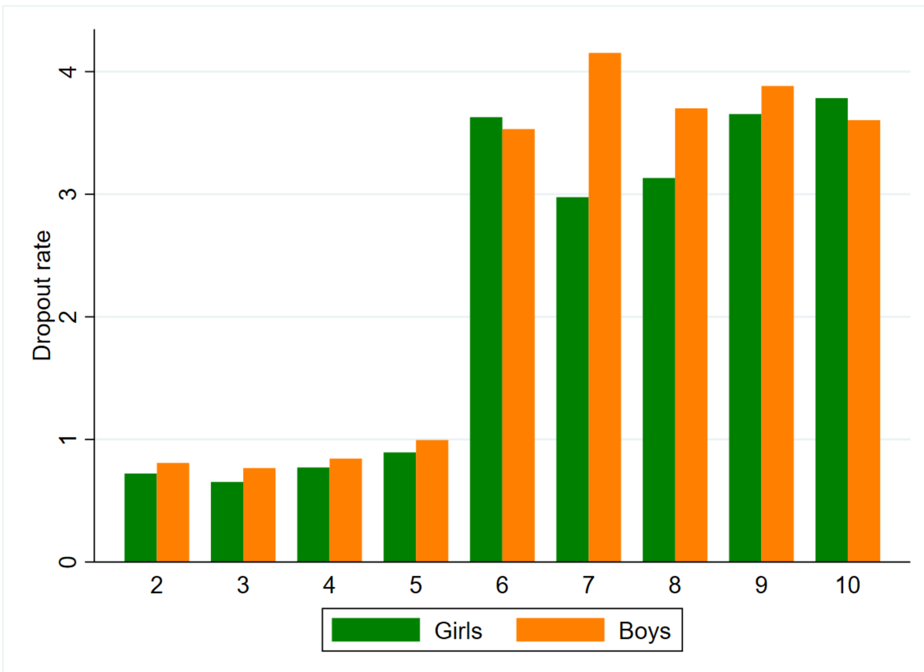
Notes: See Table 3.

APPENDIX TABLE 2: ITT Heterogenous Effects

	Female	9^{th} grade	Juntos	Parent's Schooling	Poverty	Drop-out
	PANEL A: ITT Estimates					
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	-0.0190**	-0.0117	-0.0144	-0.0123*	-0.0505***	-0.0260**
	(0.0075)	(0.0099)	(0.0172)	(0.0071)	(0.0124)	(0.0106)
No/Low	-0.0084	-0.0153*	-0.0131*	-0.0138	0.0041	0.0042
	(0.0086)	(0.0092)	(0.0069)	(0.0097)	(0.0079)	(0.0084)
	PANEL C: First-stage estimates					
Yes/High	0.5159***	0.5058***	0.3555***	0.5987***	0.4324***	0.4847***
	(0.0040)	(0.0045)	(0.0069)	(0.0040)	(0.0055)	(0.0046)
No/Low	0.5128***	0.5232***	0.5499***	0.4348***	0.5630***	0.5406***
	(0.0041)	(0.0044)	(0.0033)	(0.0041)	(0.0037)	(0.0043)

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.