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

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Abstract

This paper examines the effects of phone calls designed to encourage viewership of the short telenovela *Decidiendo para un Futuro Mejor* (Deciding for a Better Future, hereafter *DFM*) on national television during the COVID-19 pandemic in 2020 in Peru. *DFM* uses video content to highlight the benefits of education while providing concrete information on wages and financial aid opportunities for higher education. We evaluate the impact of these calls on dropout rates in 2021 through a randomized controlled trial involving over 80,000 families with high school students. Our findings indicate that the phone calls led to a significant reduction in school dropout rates, with intention-to-treat (ITT) effects of approximately −0.6 percentage points—a meaningful impact given the 10.2% average dropout rate in the control group. The effects are stronger for students from schools with higher baseline dropout and poverty rates, with no significant differences based on parental education levels. Our results also suggest that the observed effects are primarily driven by encouragement to watch *DFM* rather than by the direct impact of the phone calls themselves. These findings underscore the potential of cost-effective interventions to mitigate the adverse effects of major economic shocks on educational trajectories.

JEL Codes: D83, H52, I28, O18

Keywords: information provision, remote interventions, education, school dropouts, television, COVID.

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1 Introduction

The role of information frictions in educational decisions has been widely recognized, with interventions aimed at reducing them proving to be among the most cost-effective approaches (see World Bank, 2023b and references therein). The COVID-19 pandemic exacerbated dropout risks and learning losses, prompting various remote interventions, including phone calls, audio messages, video calls, and text messages. Many countries also relied on educational television. Information provision may be particularly relevant during crises when school attendance costs rise and perceived benefits decline. Research shows that adverse shocks impact school attendance (Jacoby and Skoufias, 1997; Bandiera et al., 2024) and that the salience of costs intensifies during periods of economic stress (Bordalo et al., 2022).

Our study contributes to the literature by evaluating the effects of educational information provision during the COVID-19 pandemic. Specifically, we examine the impact of providing educational information to Peruvian high school families. The Ministry of Education (MINEDU) adapted the *DFM* program into a televised format, broadcast nationwide in 2020 as part of *Aprendo en Casa* (*AeC*), MINEDU's primary remote learning strategy, which delivered content through online platforms, television, and radio. *DFM* employed telenovela-style videos to highlight the benefits of education, including wage returns and financial aid opportunities. Originally implemented in 2015 and 2016 as an in-person program, it demonstrated significant effects on dropout rates and other educational outcomes (Neilson et al., 2019). The *DFM* episodes aired in two one-hour sessions on September 4 and 11, 2020.

We assess the impact of encouragement calls prompting families to watch the *DFM* episodes through a randomized controlled trial (RCT) targeting urban schools with high dropout rates. The RCT included approximately 80,000 families from 1,978 schools, with 50% randomly assigned to the treatment group. MINEDU staff conducted phone calls informing families about the broadcast. Among those contacted (72.4%), 64.3% agreed to receive the message; 79.8% of them had TV access and received an encouragement to watch *DFM*, while the remaining households received a general educational message.

We use 2021 administrative enrollment data to ITT effects by comparing treatment and control groups. We also explore whether treatment effects arise from the phone calls directly or from *DFM* content, employing both OLS and regression-adjusted inverse probability weighting models (Imbens and Wooldridge, 2009). Heterogeneity analysis examines differential effects by student and school characteristics, applying both traditional analysis and machine learning techniques (Chernozhukov et al., 2018). Finally, we estimate treatment-on-the-treated (ToT) effects, using the actual delivery of the encouragement to watch the *DFM* episodes as a proxy for take-up.

Our treatment effects analyses reveal four key results. First, ITT estimates show significant dropout reductions of 0.59–0.69 percentage points from a 10.2% control group baseline. Second, evidence suggests that effects stem from the encouragement to watch the *DFM* episodes rather than direct phone call influence. Third, effects are stronger in high-dropout, high-poverty schools. Fourth, ToT estimates range from 1.14–1.34 percentage points, with no evidence that differences in take-up explain heterogeneity.

A limitation of our analysis is the lack of data on actual viewership of the *DFM* episodes among treatment and control groups, which is important for interpreting our estimates. To address this, we obtained television ratings from *TV Perú* for six major Peruvian cities, covering 54% of the urban population in

2020. The ratings for the *DFM* broadcasts were extremely low—0.15% on September 4 and 0.14% on September 11—suggesting minimal overall take-up. This implies that our ToT estimates are likely lower bounds of the effect of actually watching the episodes.

This paper contributes to several literatures. It reinforces the cost-effectiveness of educational information (World Bank, 2023b) and adds to research on remote interventions via phone calls (e.g., Angrist et al., 2022, 2023; Hassan et al., 2024). It also informs research on scaling up educational programs (e.g., Agostinelli et al., 2025; Angrist et al., 2023; Banerjee et al., 2017). While television ratings indicate low viewership, we show that encouragement calls significantly affected dropout rates. This highlights the challenges of scaling educational content through television, reinforcing the need for strategies that enhance engagement, such as embedding content in widely watched formats (Kearney and Levine, 2019, 2015) or using targeted encouragement mechanisms, like those in our intervention.

2 Background: Education in Peru and the DFM project

2.1 Education in Peru Before the Pandemic

Peru's educational system comprises three levels: early childhood (ages 2–5), primary (ages 6–12), and secondary (ages 13–17). By 2019, completion rates were 97% for primary, 92% for lower secondary, and 87% for upper secondary education (data from Peru's National Household Survey (ENAHO)—*Encuesta Nacional de Hogares*, as reported in UNESCO, 2025).[1] Despite progress, Peru lags in learning outcomes and faces significant socioeconomic disparities. In the 2018 PISA report, Peruvian students ranked near the bottom in mathematics, reading, and science at age 15.[2] Peru also exhibits one of the widest performance gaps between low- and high-income students, with the highest variance in PISA scores linked to socioeconomic conditions (OECD, 2019). National evaluations similarly show a one-standard-deviation performance gap between children from the richest and poorest quintiles (Berlinski and Schady, 2015). Ensuring secondary school completion remains a key challenge. Before the pandemic, 10.7% of children aged 12–16 in urban areas were not enrolled in secondary education in 2019. Appendix Figure 1 tracks this indicator for 2016–2023, highlighting pandemic effects on enrollment and trends by gender. Dropout rates are also closely linked to child labor (Gunnarsson et al., 2006).

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

DFM is an informational campaign developed in 2015–2016 by this research team in collaboration with MINEDU to improve several educational outcomes and behaviors. The program provided students and families with accessible information on the benefits of education, expected wage returns, and financial aid opportunities. It featured a four-episode telenovela with relatable narratives and easy-to-understand infographics based on real survey data, implemented in schools. The episodes covered key topics, including the monetary and non-monetary returns to education, financial challenges of higher education, available scholarships, loans, work-study options, and different higher education pathways. The information was sourced from ENAHO surveys and included average salaries and gender-specific data. The

[1] Completion rates follow UNESCO (2025) definitions: primary and lower secondary rates refer to children 3–5 years above the graduation age and young people aged 15–24, while upper secondary rates apply to individuals aged 20–29.

[2] 64th out of 77 in mathematics and science, and 63rd out of 76 in reading.

program targeted students from 5th grade in primary school to 5th grade in high school. Initially, it was piloted in urban and rural schools, where videos were screened in classrooms, and teachers facilitated structured discussions. Additional treatments included an app-based intervention and a component targeting parents. Appendix A provides further details on the intervention, its implementation, and treatment effects.

A formal evaluation by Neilson et al. (2019), based on randomized allocation, found significant educational benefits. The 2015 urban intervention reduced dropout by 0.2 percentage points, while the improved 2016 version led to a larger 1.8 percentage point decline over two years (18.8 percent). In rural areas, dropout rates also fell, with stronger effects for boys. Treated students reported higher educational aspirations, perceived returns, and improved academic performance. Standardized test scores increased by 3–4 percent of a standard deviation, with stronger gains in mathematics for girls. The intervention also reduced child labor, particularly among rural boys, with gender-differentiated impacts: girls benefited more in academic performance, while boys experienced stronger effects on retention and child labor reduction.

MINEDU began scaling up the program in 2015 in full-day schools,[3] but implementation varied by local capacity (e.g., scheduling within school hours) and was further disrupted by COVID-19.[4] Recently, World Bank (2023b) recognized *DFM* as a cost-effective educational intervention.

2.3 Peru and the Pandemic

Peru faced severe COVID-19 impacts, recording one of the highest excess mortality rates globally in 2020–2021, at 528.6 per 100,000 people (Knutson et al., 2022). The pandemic caused an 11% GDP decline in 2020, raising poverty from 20.2% to 30.1% (World Bank, 2021). About 6.7 million jobs were lost (World Bank, 2021), exacerbated by high labor informality (55.7% of non-agricultural jobs in 2020). Schools in Peru faced 34 weeks of full closure and 43 weeks of partial opening during COVID-19 (UNESCO).[5]

Appendix Figure 1 shows a sharp decline in secondary school enrollment in 2020, with gender differences.[6] While no direct learning loss estimates exist, test score comparisons from 2019 to 2022 (Ministerio de Educación del Perú, 2022) indicate significant declines in mathematics for 2nd and 4th graders (0.20 and 0.38 standard deviations, respectively) and in reading for 2nd graders (0.11 standard deviations).[7] To mitigate learning losses, MINEDU launched *AeC*, a multimodal education initiative designed to accommodate differences in internet access, language, and age (including an online platform, national TV broadcasts, and radio lessons in multiple languages Contraloría General de la República del Perú, 2021).

[3] Full-day schools operate on an extended schedule (45 hours per week), provide socioemotional support, and have a complex organizational structure. Introduced in 2015 with 1,000 schools, they expanded to about 2,000 by 2018, with 1,990 operating as of March 2024.

[4] As a result, *DFM* had limited impact on our study population, as the cohorts exposed to it had already progressed to higher grades or graduated by 2020.

[5] Schools closed in March 2020. By November 2021, only 2.9% of urban students were in hybrid learning (Banco Central de Reserva del Perú, 2021), with most schools reopening by March 2022 (El Peruano, 2025).

[6] Bracco et al. (2024) estimate a 5 percentage point enrollment decline in Peru during COVID-19, the largest in Latin America alongside Chile.

[7] However, secondary school results show no decline, and 8th graders even improved by 0.14 standard deviations. All these changes in tests scores are not necessarily causal. Applying causal estimates from school closure studies (e.g., Patrinos, 2023) suggests learning losses of at least 0.34 standard deviations, or approximately 1.25 years of schooling. Actually, World Bank (2023a) reports that Peruvian students lost an average of 1.7 learning-adjusted years of schooling.

3 Research Design and Methods

In this section we describe the intervention studied in this paper 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 the results from *DFM* (Neilson et al., 2019), MINEDU updated the infographics and rebroadcast the same soap-opera-style video during *AeC*. Episodes 1 and 2 aired on September 4, 2020, while episodes 3 and 4 followed on September 11, 2020 (See Appendix A for details of each episode). Therefore, this intervention occurred during nationwide school closures (March 2020–March 2022). The updated *DFM* was designed and implemented by MINEDU independently of this research team, incorporating insights from the prior intervention while adapting it for television.

The intervention encouraged families to watch *DFM* via phone calls from MINEDU personnel unaffiliated with schools. The message varied by TV access: those with access to *TV Perú* received broadcast details,[8] while others received a general message about education's importance and school contact information.[9] This (non-random) variation will help us analyze the call's effects.

The sample included students from 1,978 urban schools with high dropout rates, specifically targeting 9^{th}- and 10^{th}-grade students with at least one registered parental phone number.[10] MINEDU randomly assigned 989 schools to treatment or control groups for an *individual* phone call intervention.[11]

The treatment group comprised parents of 39,334 students, of whom 28,490 (72.4%) answered the call, and 25,290 (88.8%) agreed to receive the treatment, representing 64.3% of all households in the treatment group. Among them, 79.8% received the message inviting them to watch the program, while 20.2% received the general message.[12] In total, 51.3% of treated parents received the encouragement to watch

[8] 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 available to study in these centers. For students in 3^{rd} and 4^{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 Perú*, 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!"

[9] 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."

[10] Appendix Table 1 compares our study sample with other urban schools and rural schools. As expected, our schools differ significantly from rural schools across most dimensions. More interestingly, when compared to other urban schools, our sample includes students from larger schools in terms of both student and teacher populations. They also tend to have a slightly different boy-to-girl ratio compared to other urban secondary schools. Moreover, students in our sample are poorer due to the intervention being targeted at schools with higher dropout rates. This also implies that our sample is located in areas with a lower percentage of TV ownership and internet connections, though with greater access to cell phones.

[11] Although the treatment was implemented implemented at the household level, randomization occurred at the school level due to logistical constraints. Stratification was based on school size: small ($\leq$ 20 students in 9^{th}-10^{th} grade), medium (21–50 students), and large (>50 students).

[12] ENAHO data indicates that 74% of households in the intervention areas owned a television, aligning with this figure. See Table 1, Panel A.

DFM on TV, while 13% received the general message. Calls were made from September 1–4, 2020, with a median duration of 3.5 minutes. The encouragement calls cost approximately \$60,000 (about \$107,000 at PPP), translating to \$1.5 (\$2.7 at PPP) per student, while updating the videos, adapting them to the *AeC* format, and airing them on public television cost about \$52,000 (\$93,500 at PPP), or roughly \$0.05 (\$0.09 at PPP) per student across the two targeted cohorts.

3.2 Data

The main outcome and several covariates used in the balance checks and subsequent estimations are derived from administrative records on student enrollment for the years 2020 and 2021. Additionally, school-level information, including poverty levels, number of teachers, and other relevant characteristics, was incorporated. Take-up data for the phone calls was collected during the intervention. Furthermore, for each treatment and control student and parent, an array of educational and socioeconomic variables was obtained from administrative records. Finally, district-level socioeconomic data for the sample was sourced from the 2020 ENAHO survey.[13]

3.3 Balance

As in any randomized evaluation, we assess balance across multiple dimensions. We conduct this analysis at two levels. First, we examine balance at the school level, where we have access to a larger set of variables. Second, we assess balance at the student level for a subset of variables collected after the treatment was implemented. Table 1 presents balance on observables at both levels: Panel A reports school-level characteristics, including variables that capture the attributes of the municipalities where the schools are located, while Panel B focuses on individual-level characteristics. We find balance on most variables, with three exceptions: the share of rural schools in the area, as well as student gender and parents schooling years. However, the magnitude of these differences does not appear economically significant. For instance, the share of girls is 47.6% in the treatment group versus 49.2% in the control group, and parental years of schooling is 8.77 versus 8.66, respectively. Overall, our interpretation of these results is that there are no economically meaningful differences between the treatment and control groups across most relevant variables. Nevertheless, we will control for the unbalanced variables in our main estimates, and our results remain robust to these controls.

3.4 Statistical Methods

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

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

[13] A district is the third-level administrative subdivision, below provinces and departments, in Peru. The are 25 departments, 196 provinces, and almost 1,900 districts.

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	0.742	0.743	-0.001	0.011
% 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
Years of age	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 a TV set, 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 9th and 10th 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 *** $p < 0.01$.

where $Dropout_{is}$ is a binary indicator for whether student i in school s was not enrolled by the end of 2021. T_{is} denotes assignment to the encouragement treatment group, with β capturing the ITT effect. $\mathbf{X}_{is}$ represents a set of covariates, including strata fixed effects, school characteristics, and student characteristics, while ϵ_{is} is the error term. Although the treatment was implemented at the household level by personnel unaffiliated with the schools and delivered during a period of school closures, we cluster standard errors at the classroom level in our preferred specifications to adopt a conservative approach.

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 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[14], 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,

[14]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.

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 9th or 10th 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 10% 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 significantly reduced dropout rates, suggesting that the calls effectively motivated families to engage with the videos. This finding aligns with previous results from the *DFM* program in Peru. However, we lack data on whether households in the treatment and control groups actually watched the *DFM* episodes. This limitation is important, as the phone calls may have directly influenced dropout rates or created spillover effects. Table 3 addresses this issue by analyzing two margins: (i) treatment effects on families that received only the general message (lacking access to *TV Perú*) and (ii) treatment effects on students from the same schools who did not receive calls. In Panel A, we estimate OLS models for these subgroups, compare them to Column (4) of Table 2, and present regression-adjusted inverse probability weighting (RAIPW) estimates in Panel B to account for selection on observables.[15] Column (1) restricts the sample to families who received the "general message" without mention of *DFM* on television. The OLS estimate is 0.30 percentage points, and the RAIPW estimate is 0.34, with neither statistically different from zero. Moreover, the OLS estimate significantly differs from our main estimate in Table 2 (p-value = 0.00). Although the message content

[15] We use RAIPW because the subsamples in Table 3 are unbalanced on some socioeconomic variables, with families in the restricted treatment group typically being poorer than those in the general treatment group.

was not randomly assigned, these results suggest that the call's effects did not operate through direct messaging or general educational motivation. Thus, this serves as a placebo test for the main treatment, which specifically encouraged families to watch *DFM*. Column (2) examines an additional margin: the effects on untreated students attending the same schools as treated ones, serving as both a placebo test and a check for spillover effects. Again, treatment effects estimated via OLS and RAIPW are not statistically different from zero, and the OLS estimate differs from our main estimate (p-value = 0.00). The lack of spillover effects likely results from the school closures during this period as the treatment was individually applied, focusing on families rather than schools, as previously discussed.

TABLE 3: ITT Effects on Dropouts on 2021: Placebo and Spillover Effects

	(1)	(2)
Panel A: OLS estimates		
Treatment Dummy	0.0030	0.0062
	(0.0040)	(0.0043)
P-value of comparison with main estimate	0.0000	0.0000
Panel B: RAPIV Estimates		
Treatment Dummy	0.0034	0.0062
	(0.0040)	(0.0042)
Sample	No access to TV Peru	No Message
Observations	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 for students whose parents received the general message (without mention of the broadcasting of DFM videos on TV Peru). Column (2) 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 indicate a reduction of approximately 0.6 p.p. in dropout rates, from an average dropout rate of 10.2% in the control group. Moreover, the results in Table 3 suggest that these effects are not driven by the direct impact of the calls. These findings highlight that even modest interventions can significantly reduce dropout rates.

4.2 Heterogeneous Treatment Effects

Having established 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 (i.e., estimating treatment effects for subsamples) and employ the machine learning procedure by Chernozhukov et al. (2018).

We examine heterogeneity along the following dimensions:

- **Gender:** Examining differential effects for male and female students, as both groups may have been affected differently by COVID-19 (see Appendix Figure 1) and *DFM*, as documented in previous research (see the review in J-PAL, 2019 and Bandiera et al., 2024).
- **Grade Level:** Assessing whether impacts vary by grade level, as dropout rates tend to increase in

higher grades (Neilson et al., 2019).

- **Participation in the Juntos Program:** Using Juntos beneficiary status as a proxy for poverty.
- **Parental Education Level:** Considering whether parents' education (above/below median) affects outcomes.
- **School Poverty Levels:** Comparing schools below and above the third quintile of poverty in 2018.
- **School Dropout Rate:** Analyzing schools with dropout rates below and above the median in 2019.

Traditional heterogeneity analyses in Panel A of Figure 1 and Appendix Table 3 identify only two dimensions for which we find statistically significant differences in ITT effects: poverty and pre-COVID dropout rates at the school level. 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.

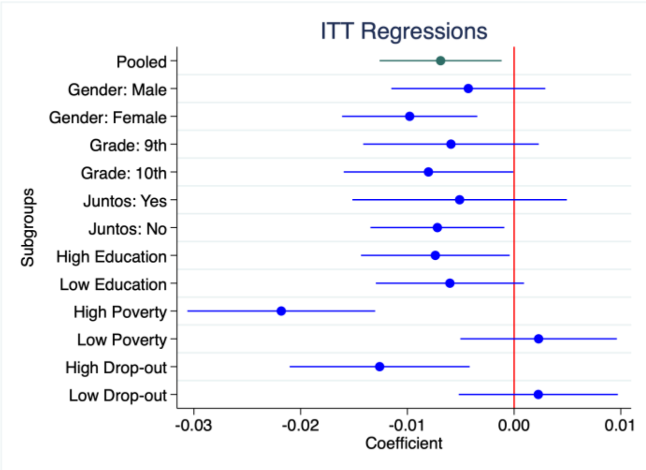
These results motivate the estimation of heterogeneous treatment effects using Chernozhukov et al. (2018)'s method, where we generate "proxy predictors" for the conditional average treatment effect (CATE). We include all covariates in $\mathbf{X}_{is}$. The Best Linear Predictor (BLP) of the CATE, average 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.

Students from schools with high poverty and high dropout rates before COVID-19 benefit the most. The least affected group has a lower proportion 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), as well as a lower proportion from high-dropout schools (0.470 in EL and 0.480 in RF) relative to the most affected group (0.546 in EL and 0.558 in RF). Gender differences indicate that female students benefit more, as shown 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). However, traditional heterogeneity analyses do not reveal statistically significant differences in effects between boys and girls. The estimated effects are -0.98 percentage points (pp) for girls (statistically significant) and -0.43 pp for boys, but the difference between these estimates is not statistically significant (p-value = 0.36). Therefore, we conclude that there is no clear evidence of differential treatment effects by gender. Similarly, differences in treatment effects by grade level, Juntos participation, and parental education are not statistically significant, consistent with the findings from traditional heterogeneity analyses.

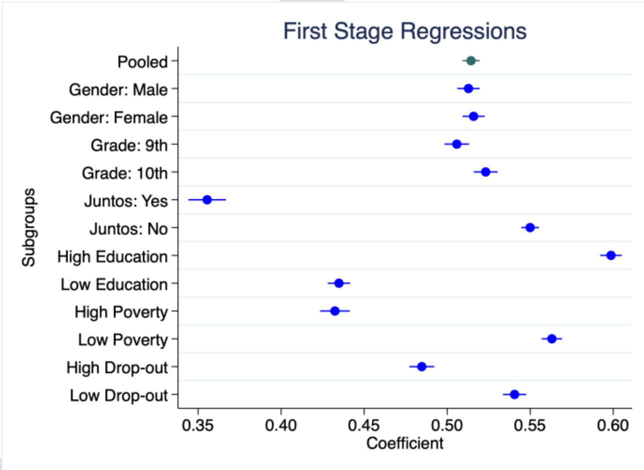
Overall, these patterns contribute to understanding the mechanisms at play and provide insights into the external validity of this type of intervention. The program was implemented during a period of severe disruption to the educational system, within a sample characterized by high dropout rates. The 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

FIGURE 1: Heterogeneity Analysis

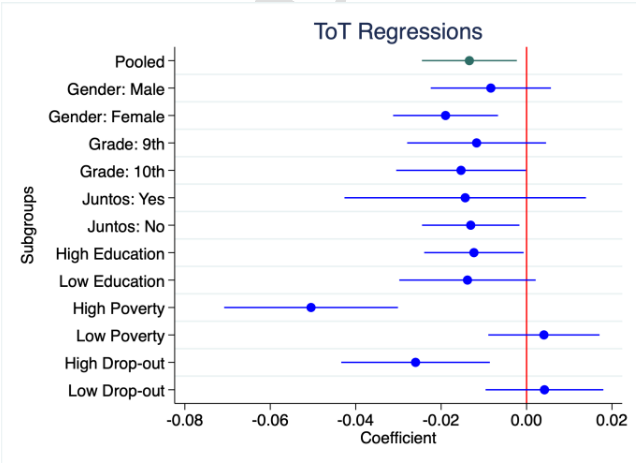
Panel A



Panel B



Panel C



Notes: Dots represent point estimates, with lines indicating 90% confidence intervals. Standard errors are clustered at the classroom level. Panel A reports ITT effects (Appendix Table 3, Panel A), Panel B presents first-stage estimates (i.e., the effect of treatment assignment on take-up; Appendix Table 3, Panel C), and Panel C shows ToT effects (Appendix Table 3, Panel B). All specifications follow those in Column (4) of Table 2. High and Low values are defined based on sample splits above and below the median value of each covariate. The red vertical line marks zero, while estimated effects for the full sample are displayed in a different color under the label "Pooled" for reference.

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 $p < 0.01$.

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.[16]

4.3 Treatment on Treated Effects

We now estimate treatment-on-the-treated (ToT) models to (i) provide estimates of the call's effect on outcomes using the encouragement design as an instrumental variable and (ii) assess whether differences in ITT effects can be attributed to variation in take-up. Our measure of take-up is a binary indicator for whether a parent received the complete treatment call. Appendix Table 2 presents ToT estimates (Panel A) and first-stage results (Panel B). The effects of treatment assignment on take-up range from 0.51 to 0.52 across all specifications, indicating that control variables do not account for differences in take-up. ToT estimates range between -1.14 and -1.34, maintaining statistical significance similar to that reported in Table 2. When district fixed effects are included in Column (5), the ToT estimate increases to -1.635.[17] Heterogeneity results in Panels B and C of Figure 1 (and Appendix Table 3) indicate that while there are statistically significant differences in take-up, they do not account for the heterogeneity in ITT effects. In summary, ToT estimates confirm significant treatment effects, with heterogeneity patterns that cannot be explained by differential take-up rates.

5 Discussion and Conclusions

The COVID-19 pandemic has disrupted educational systems worldwide, exacerbating challenges such as rising school dropout rates. This paper examines the impact of phone calls encouraging families to watch TV episodes from the *DFM* informational campaign on high-school dropout rates in Peru. The *DFM* program aimed to highlight the benefits of education and provide information on wages and financial aid. Our ITT estimates indicate a reduction in dropout rates of approximately -0.6 percentage points (p.p.) from an average dropout rate of 10.2% in the control group. ToT estimates of the encouragement call imply effects of about -1.3 p.p. in comparable specifications. This negative impact aligns with previous research on the *DFM* program (Neilson et al., 2019), though the effects are smaller, as expected, given that this was a softer implementation of the program (encouraging remote TV viewing at home versus in-person delivery at school with a teacher acting as a mediator). Because of the same reasons, the effects are also smaller than those reported in J-PAL (2019) for interventions aimed at influencing students' perceived returns to education and motivation. The average (median) estimated impact in that study is approximately 4.2 p.p. (3.2 p.p.).

A limitation of our analysis is that we do not have information on the actual viewership of the *DFM* episodes among treatment and control groups. This is crucial for interpreting the ITT and ToT effects from a policy perspective. If viewership in the control group were very high, the small ITT effect could be

[16]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.

[17]In practice, ToT estimates are Wald estimators (Angrist and Keueger, 1991), re-scaling ITT estimates by the treatment assignment dummy in the first stage, approximately 0.52.

explained by high take-up in that group. To assess this point, we obtained data from *TV Perú* on television ratings for urban areas in six Peruvian cities (Lima, Trujillo, Piura, Huancayo, Cusco, Arequipa, and Chiclayo), which represented about 54% of the urban population in 2020 and partially overlapped with our sample of urban schools.[18] Ratings measure the percentage of households watching the program relative to those with a functioning television. At the time of the *DFM* episodes, ratings were 0.15% on September 4 and 0.14% on September 11. These are very low numbers and serve as upper bounds for actual take-up, as some households may not have had a functioning television at the relevant times. These findings have two key implications for our analysis. First, our ITT effects are unlikely to be influenced by high take-up in the control group, meaning our ToT estimates represent lower bounds of the effects of actually watching the *DFM* episodes. Second, it appears that scaling up *DFM* via television was not successful in this context due to low viewership. This suggests that, to effectively scale up the provision of information through television, programs must be embedded within formats that ensure high take-up rates (as in Kearney and Levine, 2019 and Kearney and Levine, 2015) or incorporate encouragement designs similar to the one implemented in this study.

Related to this point, our study also contributes to the growing literature on phone call interventions aimed at influencing educational outcomes, particularly those implemented during the COVID-19 period. These interventions were typically related to tutoring and student support, often involving school personnel during school closures. While our intervention shares some features with these studies—such as using phone calls to encourage family engagement—it differs in key ways: it was much shorter (a few minutes versus multiple or longer calls) and did not provide content directly but rather encouraged families to watch *DFM*. Nonetheless, we can compare our results to those from other interventions. As previously discussed, the average cost per student for the encouragement design was $1.50. This compares with a cost of phone-based interventions of $12 in Angrist et al. (2023), $20 in Hassan et al. (2024), $40 in Crawfurd et al. (2021), and between $3.90 and $6.80 in Schueler and Rodriguez-Segura (2021). Notably, the interventions in Crawfurd et al. (2021) and Schueler and Rodriguez-Segura (2021) showed no significant effects on educational outcomes. Next, we evaluate whether our intervention was cost-effective. We computed cost-effectiveness in terms of Learning-Adjusted Years of Schooling (LAYS) following Angrist et al. (2020). Our treatment effects on dropout rates imply an impact equivalent to between 0.0048 (under the conservative assumption of no permanent effects on school enrollment) and 0.0072 (assuming permanent effects on school enrollment for the remaining years of secondary education). This implies that our intervention yields between 0.32 and 0.48 additional LAYS per $100. While these effects are much smaller than those in more intensive interventions—such as Angrist et al. (2023) (3.4 LAYS per $100) and Hassan et al. (2024) (3.8 LAYS per $100)—our intervention's cost-effectiveness remains non-trivial. According to Angrist et al. (2020), the estimated impact ranks in the top 20% of the 150 interventions analyzed in that paper. Furthermore, it demonstrates a higher effect per $100 than the only other intervention implemented in Peru mentioned in that study (Gallego et al., 2019), which had an effect of 0.31 LAYS per $100.

Overall, our results underscore that even modest interventions that encourage behavioral changes can have meaningful and cost-effective impacts on dropout rates, particularly during periods when dropout rates are likely to increase, as highlighted in the introduction. However, further research is needed to

[18]We thank Eduardo Guzmán and Eliseo Lock for sharing this information.

determine how best to scale up these interventions effectively and efficiently. In particular, our findings suggest that targeting higher-risk populations—those with higher poverty rates and greater expected dropout rates—could enhance cost-effectiveness. A detailed discussion on how to design optimal encouragement mechanisms for scaling up policies goes beyond the scope of this paper. However, an interesting application of such work related to phone call interventions is found in Angrist et al. (2023), which explores optimal ways to implement phone calls to support remote learning. Notably, some features of our intervention align with scalable policies, such as the use of regular MINEDU employees to conduct the calls, making the intervention more feasible at scale. Further research could explore this point in greater depth, as well as the long-term impacts of this type of interventions in different contexts and the mechanisms underlying their effects. For instance, we lack information on whether our intervention led families and students to make additional educational investments—such as engaging with other content available through the *AeC* program—which could help explain our results.

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, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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A Original DFM Program: Details and Summary of Previous Results

This appendix presents a summary of the *DFM* program and the main findings from previous research (see Neilson et al., 2019 for details). *DFM* was developed to address low educational aspirations and improve various educational outcomes by providing students and parents with accessible information about the long-term benefits of education. The intervention, implemented in 2015 and 2016, featured a four-episode telenovela with relatable narratives and easy-to-understand infographics based on real survey data.

The episodes covered:

1. *Learning the Value of Education* – The introductory episode presented the main characters and the choices they faced, emphasizing the non-monetary benefits of education.
2. *Studying to Live a Better Life* – This episode explored the financial returns of completing high school and pursuing higher education, with gender-specific data presented in the infographic.
3. *A Scholarship for My Dreams* – The characters learned about financial barriers to higher education but also discovered available scholarships, student loans, and work-study options. The infographic provided an overview of financing mechanisms, particularly the Beca 18 scholarship program in Peru.
4. *Choosing My Major, a Major Decision* – The final episode addressed different higher education pathways, providing information on the returns to various fields of study and highlighting essential 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 policy pilots in both urban and rural schools, where videos were delivered in classroom settings. Teachers facilitated screenings and guided post-episode discussions using structured materials designed to reinforce key messages. The intervention was conducted in two waves (2015 and 2016) and covered 2,611 schools in urban areas and 249 schools in rural areas. The urban intervention reached approximately 600,000 students, accounting for one-third of all secondary students and one-fourth of all primary students in urban public schools. In rural areas, where logistical challenges were greater, the program targeted fifth and sixth graders in high-poverty districts of Cusco and Arequipa, reaching approximately 5,000 students. In urban areas, compliance with the intervention in 2015 was low, with only 43 percent of schools receiving the video materials. Among those, just 75 percent actually screened them, leading to an effective take-up rate of 33 percent. In response, the 2016 implementation introduced monitoring mechanisms, including call centers, direct school visits, and incentive structures, which increased the take-up rate to 67 percent. In rural areas, where implementation involved centralized screenings conducted by field staff using portable projectors, compliance was nearly universal.

Additional treatments included an app-based intervention known as In-Depth Tablet (IDT), which provided personalized educational content and enabled real-time assessment of students' perceptions. The app was deployed among 3,334 students in urban areas and 3,000 in rural areas, with a randomly selected subset of parents (1,816 urban and 993 rural) receiving a parallel intervention designed to engage them in their children's education.

A formal evaluation by Neilson et al. (2019), based on the random allocation of schools and students to treatment, found significant positive effects across multiple educational outcomes. The 2015 urban intervention led to a modest 0.2 percentage point reduction in dropout rates among fifth and sixth graders, while the improved 2016 implementation resulted in a larger reduction of 1.8 percentage points over two years—a relative decrease of 18.8 percent. In rural areas, the intervention significantly reduced both one-year and two-year dropout rates, with stronger effects observed among boys. Additionally, treated students exhibited increased educational aspirations and higher perceived returns to education.

Beyond enrollment, *DFM* had a measurable impact on academic performance. Treated students showed significant improvements in national standardized test scores. Specifically, scores on the Evaluación Censal de Estudiantes (ECE) increased by 3 to 4 percent of a standard deviation, with particularly strong gains in mathematics performance among girls. These improvements suggest that the intervention not only affected retention but also positively influenced student learning.

Another key outcome analyzed was the effect of the intervention on child labor. *DFM* led to a significant reduction in the likelihood of children engaging in labor, particularly among boys in rural areas. This suggests that the program influenced household decision-making, reducing the need for students to contribute to household income through work. The intervention also produced gender-differentiated effects. While both boys and girls benefited from the program, results indicate that girls experienced greater improvements in academic performance, particularly in mathematics, while boys exhibited stronger effects on school retention and child labor reduction.

APPENDIX TABLE 1: Comparison of RCT Sample with Other Urban and Rural Schools

	(1) RCT Sample	(2) Other Urban Schools	(3) Difference	(4) Rural Schools	(5) Difference
Total students	286.015	205.267	80.747***	64.967	221.047***
Percentage of female students	47.597	47.076	0.522**	46.856	0.742***
Total female students	136.700	102.456	34.244***	30.449	106.251***
Total male students	149.314	102.811	46.504***	34.518	114.796***
Total teachers	8.396	5.965	2.432***	3.322	5.074***
Rural	0.000	0.000	0.000	1.000	-1.000
Private School	0.000	0.600	-0.600***	0.034	-0.034***
Percentage of Students with Low Income	0.439	0.241	0.198***	0.723	-0.284***
Percentage of Students with Middle Income	0.280	0.311	-0.031***	0.096	0.184***
Percentage of Students with High Income	0.170	0.387	-0.217***	0.036	0.134***
% TV ownership	0.746	0.862	-0.116***	0.526	0.220***
% Internet connection	0.205	0.277	-0.073***	0.086	0.119***
% Cellphone ownership	0.634	0.616	0.019***	0.633	0.001
Observations	1,978	8,468		4,385	

Notes: This table includes only secondary schools. The columns labeled "Difference" compare the RCT sample with other urban schools and the sample of rural schools. From ESCALE (Educational Unit Statistics), we calculate the following variables: *Total students* refers to the total number of students in a school, while *Percentage of female students* indicates the proportion of female students. *Total female students* and *Total male students* represent the total number of female and male students, respectively. *Total teachers* refers to the total number of teachers. *Rural* is a binary indicator of whether the school is in a rural area, and *Private school* is a dummy variable indicating whether the school is private. Finally, *Percentage of students with low income, middle income, and high income* represents the school's share of students in low-, middle-, and high-income groups. *% TV ownership*, *% Internet connection*, and *% Cellphone ownership* represent the share of households in the district that own a television, have internet access, and own a cellphone, respectively. These indicators were calculated using data from the National Household Survey (ENAHO 2019).
* $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

APPENDIX TABLE 2: 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

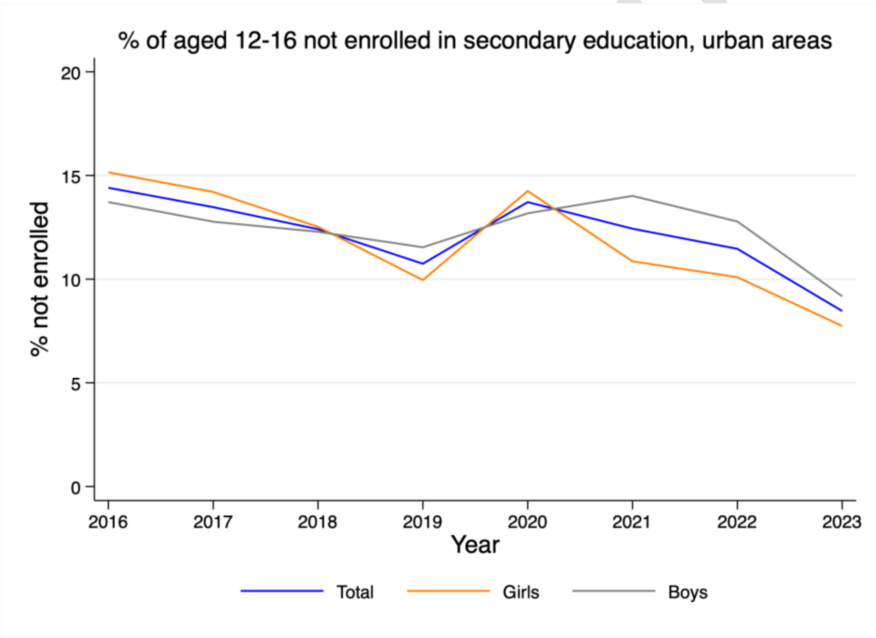
Notes: See Table 3.

APPENDIX TABLE 3: Heterogenous Effects

	Female	9^{th} grade	Juntos	Parent's Schooling	Poverty	Drop-out
	PANEL A ESTIMATES: 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)
P-value	0.3583	0.7153	0.5511	0.7443	0.0004	0.0230
	PANEL B ESTIMATES: 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*	-0.0126	-0.0138	0.0041	0.0042
	(0.0086)	(0.0092)	(0.0082)	(0.0097)	(0.0079)	(0.0084)
P-value	0.3576	0.7323	0.7922	0.9581	0.0002	0.0329
	PANEL C ESTIMATES: 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)
P-value	0.6789	0.0047	0.0000	0.0000	0.0000	0.0000

Notes: Panel A presents ITT effects, Panel B presents ToT effects, and Panel C presents first stages (i.e., 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. The "P-value" rows correspond to tests of equality of effects for each split of the sample. All specifications include the same set of covariates as in column (4) of Table 2, 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), and 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. * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$.

FIGURE APPENDIX 1: Children Not Enrolled in Secondary Education, Urban Areas, 2016–2023



Notes: Data computed by MINEDU from the ENAHO surveys, retrieved from https://escale.minedu.gob.pe/ueetendencias2016.

Highlights

- Phone calls encouraging TV-based education reduced dropout rates during COVID-19.
- Effects were strongest in high-poverty and high-dropout schools.
- Low TV ratings suggest limited take-up without active encouragement.
- Results highlight the need for targeted interventions to scale TV-based education.
- Cost-effective design provides insights for future remote learning policies.

DISCLOSURE STATEMENT

March 13, 2025

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To the Editorial Board,

We declare that we have no relevant or material financial interests that relate to the research described in the paper entitled "Lights, Camera, School: Information Provision through Television during COVID-19 Times"

Sincerely,

Francisco A. Gallego
Oswaldo Molina
Christopher Neilson