

Free to Choose

Introducing Technology for
Foundational Learning in Pakistan

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Technology and takeup

Multiple views on the benefits/costs of technology in the classroom

- Positive: can change the world
- Negative: Neutral or even increases digital divide (meta-analysis in the U.S. shows generally zero impact).

One key consideration is whether these studies compare apples with apples in terms of how often the technology is *taken-up*

- 96% of students tried Khanmigo, but substantive math dialogue remained rare (Oreopoulos and Low, 2026)
- Take-up and teacher versus volunteer delivery explain much of TaRL's varying impact. (Angrist and Meager, 2023)
- Takeup related to students who were already more prepared (Robinson, Bisht, and Loeb, 2025)
- Dedicated lab staff raised Khan Academy use and math achievement in Uttar Pradesh. (Oreopoulos, Keyes-Krysakowski, and Agarwal, 2026)
- Integrating Mindspark into public school schedules raised math and Hindi scores. (Muralidharan and Singh, 2025)

Is take-up limiting scale?

The scaling assumption

If 20% take-up produces an effect of X , then 40% take-up produces $2X$.
This holds when treatment effects are not heterogeneous.

Supply-side barriers

Removing barriers to access may increase take-up and improve outcomes.

Demand-side selection

Roy's model predicts that non-users may gain less from technology than those who choose to adopt it.

Impact at low take-up may be an upper bound on average impact at scale, offering an explanation for the “voltage drop” from scaling (List).

A striking example: Targeted Instruction Program in KP

- As a first step, we compare teachers under technology treatment arm 1 with control group

The take up of technology is around 65% (46% if measured by usage), and the program yields a 0.18 SD gain

The program gain suggests that technology has a beneficial impact, but it can be scaled-up further

- To scale-up further, we introduce treatment arm 2 with the aim to increase technology takeup

Take up increases to 84% (67% if measured by usage)

The program gain drops to 0.09 SD compared to control group

- We implement a scale-up technology in Arm 2 that indeed increases technology usage, but we get a marginal “**voltage drop**”

Research questions

1. What explains the result in theory?

Endogenous selection into treatment on the demand side.

2. Can an experiment test this mechanism?

Varying how technology is introduced allows us to assess the predictions of the theory.

The TIP results show why increasing technology take-up need not scale up learning gains.

Theory

Observed difference = ATT + Selection bias

$$ATT = E[Y(1) - Y(0) \mid D = 1]$$

$$\text{Selection bias} = E[Y(0) \mid D = 1] - E[Y(0) \mid D = 0]$$

Selection bias asks whether the people who actually receive treatment would have had different outcomes from untreated people even in the absence of treatment.

IV interpretation

Under standard IV assumptions (instrument independence, exclusion, relevance, and monotonicity), the Wald estimator identifies the treatment effect on compliers.

Here, compliers are teachers who use technology when mandated but would not use it if given the option.

A striking example: TIP in KP

Intervention	40-day remedial targeted instruction program to all primary grade students in foundational literacy (English, Urdu) and numeracy (Math) The program was during normal schools hours by existing teachers.
Sample	1,250 public primary schools, 7,000 teachers, and over 250,000 from grades 1 - 5 in KP Province Pakistan <u>Note:</u> Research sample is 2,920 teachers and 24,730 4th grade students at 916 public primary schools. Schools are gender segregated (514 male, 402 female schools). All treated teachers were trained, and given lesson plans, learning aids, quiz and workbooks and activity aids. All treated teachers received support from mentors during the program.
Experimental Design School based randomization	● Control, did not implement the TIP program ● Mandated Tech, teachers delivered the program with access to a smartphone based assistive technology. They were required by the education department to use the technology regularly ● Paper (No Tech), teachers delivered the program with paper-tracking tools in lieu of the technology tool ● Optional Tech, teachers delivered the program with access to the technology but were given the flexibility to either use it or use paper-tracking tools as they saw fit.

Treatment 1: Technology adoption is Optional

Measuring technology take-up by opening tech tool account / using quiz entry feature

	Arm 1 (Optional Tech)
Teachers opened tech tool account	65%
Teachers undertook quiz entry	46%
Child Test-score gain ITT (vs control)	0.18 SD

Full take-up, assuming unchanged gains:

Technology has a beneficial impact; assuming proportional gains, it could be potentially scaled up further.

A striking example: TIP in KP

Wald ratio = difference in mean test scores / difference in technology take-up
Measuring technology take-up by opening tech tool account / using quiz entry feature

	Arm 2 (Mandated Tech)
Opened tech tool account	84%
Quiz entry	67%
Test-score ITT vs. control	0.09 SD

Arm 2 vs Arm 1: $-0.09 / 0.21 = -0.43$ SD

Voltage drop

Increasing take-up significantly lowers student scores among teachers induced to adopt.

The First Stage: Increasing technology takeup

Technology take-up measures. Preferred measure: quiz entry.

Technology use	Opened tech account	Training modules	Formed or reassigned peer groups	Checked off or downloaded lesson plans	Entered quiz scores
Arm 2: Take-up, Mandated	0.843	0.406	0.468	0.811	0.666
Arm 1: Take-up, Optional	0.646	0.296	0.371	0.623	0.463
First-stage estimate	0.197*** (0.035)	0.110*** (0.029)	0.097*** (0.035)	0.188*** (0.038)	0.202*** (0.033)

1,696 teachers in mandated tech and optional tech arm. SE in parentheses.

Mandating technology increases tech take up by 20.2 percentage points.

Second Stage: Selection into technology

Effect on compliers

Teachers who adopt when mandated but would opt out under optional access.

Student scores fall for both definition of compliers.

−0.39 SD

Technology take-up

Opened a technology account

Instrument variable: Mandated vs Optional assignment.

−0.42 SD

Quiz entry

Entered quiz scores at least once

Characteristics of Compliers

	Obs.	All	Complier	Always-taker	Never-taker	C – A	C – N	A – N
Share of Teachers			0.202	0.463	0.334			
Male School	1696	0.598	0.526 (0.172)	0.626 (0.047)	0.628 (0.044)	-0.100 [0.625]	-0.102 [0.517]	-0.002 [0.973]
Teacher's Age	1657	39.26	36.43 (1.84)	38.42 (0.53)	41.72 (0.52)	-1.99 [0.372]	-5.29*** [0.005]	-3.30*** [0.000]
Teacher First Hired >2013	1657	0.529	0.570 (0.114)	0.602 (0.033)	0.393 (0.032)	-0.032 [0.815]	0.176 [0.131]	0.209*** [0.000]
Teacher Has STEM Degree	1657	0.231	0.194 (0.099)	0.310 (0.024)	0.094 (0.018)	-0.116 [0.310]	0.100 [0.311]	0.216*** [0.000]
Has Master's Degree	1657	0.615	0.692 (0.098)	0.635 (0.028)	0.543 (0.034)	0.057 [0.629]	0.149 [0.145]	0.092** [0.039]
District	1696	0.457	0.219 (0.185)	0.552 (0.045)	0.482 (0.046)	-0.333 [0.121]	-0.263 [0.126]	0.070 [0.292]
Urban=1,Rural=0	1696	0.227	0.163 (0.171)	0.273 (0.046)	0.230 (0.043)	-0.110 [0.587]	-0.067 [0.667]	0.043 [0.490]
School Size (0=small,1=large)	1696	0.571	0.689 (0.172)	0.552 (0.046)	0.617 (0.044)	0.137 [0.498]	0.072 [0.644]	-0.065 [0.313]
Confidence in Tech Device	1482	0.474	0.505 (0.118)	0.490 (0.032)	0.403 (0.038)	0.014 [0.920]	0.102 [0.393]	0.088* [0.075]
Confidence in Tech Software	1459	0.477	0.629 (0.116)	0.478 (0.029)	0.380 (0.040)	0.151 [0.263]	0.249** [0.040]	0.098* [0.053]

- Compliers tend to be younger teachers
- Always takers are younger, more likely to be hired under the new scheme (2014 and onward), with STEM degree, has Master's degree, and are confident with tech device/software compared to never takers.

endogenous variable: used quiz score feature in tech tool

Conclusion and Caveats

- With heterogeneous treatment effects, scaling up through increasing take-up may not work.
- The IV works under an exclusion restriction: the optional vs. mandated treatment effects outcomes only through teachers' choices.
 - Not an “empowerment effect” that having an option may have on teachers, whether or not they choose the technology.

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Appendix

Endline ITT

Outcome: endline mean test score (SD). Each arm compared with Control.

	(1) Mandated	(2) Optional	(3) Paper
Mandated	0.0853** (0.04)		
Optional		0.176*** (0.04)	
Paper			0.0963** (0.04)
Baseline mean test score	0.530*** (0.02)	0.517*** (0.02)	0.543*** (0.02)
Urban school	−0.0509 (0.05)	−0.0208 (0.05)	−0.0441 (0.04)
Male School	−0.158*** (0.04)	−0.207*** (0.04)	−0.171*** (0.04)
Peshawar District	0.0483 (0.04)	−0.0501 (0.04)	0.0660* (0.04)
Large School	0.0448 (0.05)	0.0992** (0.05)	−0.00869 (0.05)
Constant	0.420*** (0.06)	0.434*** (0.05)	0.471*** (0.05)
Observations	10,699	10,985	11,165
R ²	0.34	0.35	0.37

OLS. Standard errors in parentheses, clustered by school.

* p < 0.10, ** p < 0.05, *** p < 0.01

TOT using quiz entry

Outcome: endline mean test score (SD). Account take-up shown for comparison.

	(1) Account take-up	(2) Quiz entry
Opened technology account	0.0694 (0.05)	
Entered quiz scores at least once		0.0974 (0.08)
Baseline mean test score	0.567*** (0.02)	0.563*** (0.02)
Urban school (1 = urban)	0.00821 (0.04)	0.00737 (0.04)
Male school	−0.165*** (0.04)	−0.166*** (0.04)
Peshawar	−0.0456 (0.04)	−0.0498 (0.04)
School size (1 = large)	0.0588 (0.04)	0.0613 (0.04)
Constant	0.556*** (0.04)	0.556*** (0.04)
Observations (teachers)	1,343	1,343
R ²	0.44	0.44

2SLS. Standard errors in parentheses, clustered by school.

* p < 0.10, ** p < 0.05, *** p < 0.01

Potential Outcomes Table

- We can then define the following 3 objects
- The *Average Treatment Effect* or

$$ATE = E(\delta_i) = E(Y_i^1 - Y_i^0) = E(Y_i^1) - E(Y_i^0)$$

- The *Average Treatment on Treated*

$$ATT = E(\delta_i | D_i = 1) = E(Y_i^1 - Y_i^0 | D_i = 1) = E(Y_i^1 | D_i = 1) - E(Y_i^0 | D_i = 1)$$

- The *Average Treatment on Untreated*

$$ATU = E(\delta_i | D_i = 0) = E(Y_i^1 - Y_i^0 | D_i = 0) = E(Y_i^1 | D_i = 0) - E(Y_i^0 | D_i = 0)$$

- The ATE is a weighted average of ATT and ATU so that

$$ATE = p.ATT + (1-p).ATU, \text{ where } p \text{ is the proportion with } D_i = 1$$

Potential outcomes and Omitted Variable Bias

- Researchers never observe the same person with and without the treatment or Y_i^1 and Y_i^0
- Instead, they observe $(Y^1|D = 1)$ and $(Y^0|D = 0)$
- What can be estimated from the data is instead: $E(Y^1|D = 1) - E(Y^0|D = 1)$
- It can then be shown (see Cunningham Chapter 4) that the Simple Difference in Outcomes or

$$\begin{aligned} & \text{SDO} \\ & = \\ & E(Y^1|D = 1) - E(Y^0|D = 1) \\ & = \\ & \text{ATE} + E(Y^0|D = 1) - E(Y^0|D = 0) + p \cdot (\text{ATT} - \text{ATU}) \end{aligned}$$

where p is the proportion with $D_i = 1$

Solving the Omitted Variable/Selection Problem

- Consider the simple case of a treatment that can take the value 0 or 1, so $D=1$ or $D=0$
 - (Note that in this case, the regression is just the comparison of means: $E(Y|D=1) - E(Y|D=0)$)
- **Randomizing** the units that receive treatment fully solves the omitted variable problem
- **Why?**
 - Regression framework: $\widehat{\beta}_1^{SR} - \beta_1^{LR} = \beta_2^{LR} * \pi_1$, where π_1 is the coefficient from the Auxiliary Regression: $X_2 = A + \pi_1 D + \delta$. But if D is randomly allocated, then, by definition $\text{Cov}(X_2, D) = 0$ —there cannot be any relationship between X_2 and D in theory (there still could be by chance—that's the problem of inference!)
 - But if $\text{cov}(X_2, D)=0$, then $\pi_1 = 0$, which implies that : $\widehat{\beta}_1^{SR} = \beta_1^{LR}$
- In principle then, randomizing the treatment units fully solves the omitted variable problem!
 - This does not solve problems of inference—which we will discuss.
 - The precise form of the randomization can be complicated
- What about in the potential outcomes framework?

Solving the Omitted Variable/Selection Problem

- Consider the simple case of a treatment that can take the value 0 or 1, so $D=1$ or $D=0$
- $SDO = ATE + E(Y^0|D = 1) - E(Y^0|D = 0) + p.(ATT-ATU)$
- Note that
 - $E(Y^0|D = 1) - E(Y^0|D = 0) = 0$ by virtue of randomization. Because, on average the $D=1$ and $D=0$ group are identical, it must be that their outcome if they had not received the treatment would have been the same on average!
 - $ATT = E(Y_i^1|D_i = 1) - E(Y_i^0|D_i = 1)$
 - $ATU = E(Y_i^1|D_i = 0) - E(Y_i^0|D_i = 0)$
 - $ATT-ATU = E(Y_i^1|D_i = 1) - E(Y_i^0|D_i = 1) - \{E(Y_i^1|D_i = 0) - E(Y_i^0|D_i = 0)\} = \{E(Y_i^1|D_i = 1) - E(Y_i^1|D_i = 0)\} + \{E(Y_i^0|D_i = 1) - E(Y_i^0|D_i = 0)\}$
 - By the same logic, each of the terms in the curly brackets is 0! So, if D is randomized, it must be that the $SDO = ATE!!!$
- This is why randomization holds particular appeal—it solves the omitted variable problem without requiring lots of assumptions and additional structure on the problem