Explaining the Productivity Paradox

Experimental Evidence from Educational Technology

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To Avanti Fellows,
the Government of Haryana and Haryana’s school administrators, teachers, and students,
Harvard University, J-PAL, MIT, MSDF, USAID, and my advisors:

Thank you.
Introduction
The productivity paradox remains unresolved—

"You can see the computer age everywhere but in the productivity statistics."

Solow (1987)
—nowadays, we just call it the *modern* productivity paradox.

"We thus appear to be facing a redux of the Solow (1987) paradox:

*We see transformative new technologies everywhere but in the productivity statistics.*

Brynjolfsson et al. (2017)
EdTech: A prime example of why it is so hard to isolate the effect of technology

Does Educational Technology (EdTech) indeed serve a purpose of either factor-augmenting or complementary technology?

EdTech investments often lead to an increase in instructional inputs, instructional time.

Muralidharan et al. (2019); Angrist et al. (2022)
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Fabregas (2018); Jamison et al. (1981); Johnston and Ksoll (2022); Naik et al. (2020); Navarro-Sola (2019); Seo (2017)
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Most commonly: A mixture of changes in study time, substitution of teacher-led instruction, and adjustments to instructional technology.

Araya et al. (2019); Banerjee et al. (2007); Carrillo et al. (2010); Lai et al. (2015); Linden (2008); Taylor (2018)
An RCT to measure the causal effects of an EdTech program that encourages Indian teachers to blend their instruction with high-quality video materials.

- Largest cluster-randomized trial studying EdTech as a potential complement to teaching, largely shutting down other channels
- In comparison to a non-tech program; detailed obs. of mechanisms (1,500+ classroom obs.)
- In partnership with a state government, across 240 schools, 25k+ students

I find negative effects of the EdTech intervention on math, no effects on science learning, no effects of non-tech intervention, after 11 months.

• ITT effects of -0.15 SD in math, for the intervention promoting blended instruction
• Implementation failure ruled out; negative effects on instruction, student attitudes
• Consistent with adjustment costs as an explanation for the productivity paradox
This study: What I do and what I find

An RCT to measure the causal effects of an EdTech program that encourages Indian teachers to **blend their instruction** with high-quality video materials.

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2/ Context and intervention
Our setting is the scale-up of a public-private partnership in Haryana’s public secondary schools.

Figure 1: Location of the study

Notes. This figure depicts the state of Haryana (in light blue) and the eight districts selected for the study (highlighted in red).
The intervention provides monthly, on-site coaching to promote blended instruction in math, science.

Figure 2: Intervention components

(a) Information and Communication Technology (ICT) infrastructure, video materials

(b) Workbooks, pedagogy
3/ Research design and analytical strategy
We conduct a 3-arm, cluster-RCT, comparing the EdTech program against the non-tech alternative and a business-as-usual control group.

Figure 3: Study schools by treatment status

Notes. This figure depicts the 240 study schools by experimental status. Red dots indicate ICT schools (T1), dark gray indicates workbook-only schools (T2), and white indicates control schools. Stratified randomization within triplets of matched schools. 10 re-randomizations to increase balance across T1, T2, and C, following a “min-max” strategy (cf. Banerjee et al., 2020; Bruhn and McKenzie, 2009).
Our main outcome of interest is student learning in mathematics and science

**Main outcome**

- *Written assessments*: Group-administered; paper-based; ~60 multiple choice questions (two hours).

- Linked with a two-parameter Item Response Theory (IRT) model.
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Secondary outcomes

• *Sub-competencies in content domains*: 4 domains in math (e.g., algebra vs. geometry), 3 domains in science (biology, chemistry, physics).

• *Sub-competencies in cognitive domains*: Higher-order vs. lower-order thinking skills (HOTS/LOTS).
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We collect additional data guided by the program’s Theory of Change

**Implementation fidelity**

- *Teaching and learning materials*: (1) Classroom observations; (2) student surveys; (3) backend data from the software.

- *Teacher training (offsite), monitoring and coaching (on-site)*: (1) Attendance records; (2) an application documenting all work done by NGO staff.
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**Intermediate outcomes**

- *Instructional behaviors and quality:* 
  (1) Classroom obs. *(Stallings, QUIP)*; (2) teacher, student surveys

- *Student attitudes towards mathematics, science:* 
  Student survey
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[QUIP] [Student survey]
We estimate intent-to-treat effects with OLS regressions

\[ Y_{isv} = \alpha + \sum_{k=1}^{2} \beta_k T_{ksv} + X_{isv} + \phi_r + \epsilon_{isv} \] (1)

- \( \beta_k \) captures the intent-to-treat (ITT) effect of each program variant \( k \), for follow-up round \( t \), for student \( i \) in school \( s \), in village \( v \), and randomization stratum \( r \).
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- \( \beta_k \) captures the intent-to-treat (ITT) effect of each program variant \( k \), for follow-up round \( t \), for student \( i \) in school \( s \), in village \( v \), and randomization stratum \( r \).
- \( t \) refers to a baseline (\( t = 1 \)), and an endline after 11 months (\( t = 2 \)).
- To increase precision: \( X_{isvr}^{t=1} \) as covariates.
- \( X_{isvr}^{t=1} \): vector of baseline controls selected through a Lasso procedure, from \( Y_{isvr}^{t=1} \), student age, gender, school-level admin. data (“DISE”), and village-level census data.
- Randomization strata fixed effects \( \phi_r \) included. Standard errors clustered at the school level.
The sample is similar to India’s population of gov. schools; randomization led to three similar groups.

Representativeness

• I compare study schools with the universe of India’s government secondary schools (on census village characteristics, school characteristics, National Achievement Survey, State board exams).

• Study schools are positively selected within the state, but fairly representative of India.
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Balance

• No differences in attrition: 24 percent to endline; balanced across the three groups.

• Baseline balance, on time-invariant observables (1/24 tests of village-, 2/27 tests of school-level characteristics, no difference in board exams or student demographics).

• Baseline imbalance for test scores for one group comparison (Workbook vs control); included as control, does not affect the results in robustness checks.
Key components of the intervention were implemented as intended and taken up well.

1. ICT infrastructure upgrades implemented as planned.

2. Videos installed, used (slightly less in math).

3. Workbooks distributed and used, outside the classroom.

4. Limited use of in-class exercises, peer learning, in both groups.

5. Limited on-site coaching (anecdotal).
4/ Results
After 11 months of the ICT intervention, I find negative effects on math, no effects on science test scores.

**Notes.** All estimations include randomization strata fixed effects and a vector of school- and village-level covariates, selected via LASSO. Horizontal bars show confidence intervals (s.e.s clustered at the school level).

**Sample.** 18,562 grade-9 and grade-10 students.
Following a registered Pre-analyis Plan, I report additional results for effects on test scores

1. Results are similar for higher- vs lower-order skills.  

2. Grade-9 students and weaker students are affected only slightly more negatively (in math).  

3. Math effects are only slightly larger for below-level material; otherwise uniform across domains.
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3. Math effects are only slightly larger for below-level material; otherwise uniform across domains.
4. There is limited heterogeneity across districts.
I find negative effects of the ICT intervention on the quality of instruction students receive.

Figure 5: ITT effects on instructional quality

Follow-up differences
In-person (Avanti)

Horizontal bars show confidence intervals (s.e.s clustered at the school level).

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Sample. 1,343 classroom observations in mathematics and science.
For both treatment arms, I find negative effects on student perceptions, attitudes

Figure 6: ITT effects on student perceptions, attitudes

Notes. All estimations include randomization strata fixed effects and a vector of school- and village-level covariates, selected via LASSO. Horizontal bars show confidence intervals (s.e.s clustered at the school level).
Sample. 1,214 student interviews.
Conclusion
• I observed **negative effects** on instructional quality, student attitudes; **negative to null effects** on student learning.
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My findings suggest **introducing new Information and Communication Technologies may disrupt**, lead to substantial adjustment costs—at least in the short run.

It will be worthwhile observing long-term effects—are there positive returns on these costly adjustments?

Currently, (post) Covid-19 studies on EdTech should invest in additional efforts to isolate mechanisms and be cautious about the potential disruption of instruction.
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Impact and next steps

- The NGO pivoted and turned the math intervention into a remote, after-school program. It tries to improve the science intervention over time.

With funding from USAID and MSDF, I study the effects of both interventions in a new cohort of children.

The Haryana government invited me to join an expert panel that consulted on the state’s provision of a tablet-based EdTech program to 1m+ public school children.
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Appendix
We purposely sampled 240 secondary schools, following an infrastructure survey.

Figure A1: Sample of 240 government senior secondary schools

Notes. This figure depicts the 240 senior secondary government schools purposely selected for the study.
The written tests do not suffer from ceiling or floor effects

Figure A2: Empirical distribution of test scores, by subject

Notes. This figure provides the empirical distribution of test scores, as per 2PL IRT models, for students. Each panel shows kernel density plots, by experimental group, at baseline.
The written tests measure with high levels of precision, across the ability distribution.

Figure A3: Test information functions (TIFs)

Notes. This figure provides the test information functions, and corresponding standard errors of measurement, for the mathematics and science tests, as per 2PL IRT models.
The two-parameter logistic IRT model

The two-parameter logistic (2PL) model predicts the probability of correctly answering each test question (or “item”) \( i \), given student’s \( j \) ability \( \theta \) and two item parameters: item discrimination \( a \) and item difficulty \( b \).

\[
P_{ij} (\theta_j, b_i, a_i) = \frac{\exp \left[ a_i (\theta_j - b_i) \right]}{1 + \exp \left[ a_i (\theta_j - b_j) \right]} \tag{2}
\]

- Assigns different weights to individual test questions.
- Allows for linking of ability estimates onto a common scale, across assessment rounds and grades.
- Provides information on measurement error across the ability distribution.
- Estimated via marginal max. likelihood (MML).
We measure instructional behaviors, quality with the **QUIP** classroom observation instrument

Figure A4: **QUIP** framework

Notes. This figure reports on the distribution of QUIP scores, showing histograms for each QUIP element.
We measure instructional behaviors, quality with the *QUIP* classroom observation instrument (ctd.)

**Figure A5: QUIP framework**

*Notes.* This figure provides a kernel density plot of the QUIP index score. “Index” refers to the inverse covariance matrix-weighted aggregate across the six elements.
We measure student attitudes towards mathematics with one-on-one interviews.

We calculate an inverse covariance matrix-weighted index, for the following items:

- Student enjoys learning math
- Student finds math easy to understand
- Math makes the student nervous (reversed)
- Student finds math harder than other subjects (reversed)
Through GIS, we link India’s EMIS to village-level censuses and satellite-recorded nightlights data.
Results are robust to dropping the seven most severely imbalanced randomization triplets.

Figure A7: Balance on baseline test scores before/after dropping imbalanced strata.

(a) Mathematics

(b) Math (adj.)

(c) Science

(d) Science (adj.)
ICT infrastructure installed and functional—the other schools do not have ICT programs.
Teachers use the video materials—including on days without school visits

Figure A9: Video usage, by subject (in minutes)

(a) Math

(b) Science
Workbooks were distributed and they are used (outside the classroom)

Figure A10: Availability and use of workbooks, in-class exercises, by treatment group

Follow-up mean

- Workbooks distributed
- Shortage of workbooks
- Student can produce workbook
- Student started using workbook
- Student uses workbook in 'every class'
- Workbook checked by teacher
- Workbook not at all used in class
- Conducted in-class exercise
- Students involved in exercise

ICT Workbook

Follow-up mean

0.0 20.0 40.0 60.0 80.0 100.0
Effects are similar across higher-order and lower-order skills

Figure A11: ITT effects on student learning by cognitive domain
Effects are similar across curricular grade-levels and across content domains

Figure A12: ITT effects on student learning by content domain
Figure A13: Heterogeneous ITT effects on math learning
Figure A14: Heterogeneous ITT effects on science learning

Control-group growth

By grade
- Grade 9
- Grade 10

By baseline learning level
- Bottom tercile
- Middle tercile
- Top tercile

Follow-up differences

By grade
- Grade 9
- Grade 10

By baseline learning level
- Bottom tercile
- Middle tercile
- Top tercile

- ICT vs Control
- Workbook vs Control
Figure A15: Heterogeneous ITT effects on math learning

(a) ICT vs Control

(b) Workbook vs Control
Test scores: Effects by district, in science

Figure A16: Heterogeneous ITT effects on science learning

(a) ICT vs Control

(b) Workbook vs Control
NGO-administered ratings provide an upper bound for effects on instructional quality

Figure A17: ITT effects on instructional quality (adjusted)

Index

Monitoring of student learning
Feedback
Management of class time
Dense focus on math/science
Clarity, lack of errors
Richness

Follow-up differences
In-person (Avanti)

Follow-up differences
Adjusted (Video-based)

ICT vs Control
Workbook vs Control

Back
The ICT intervention increased EdTech usage; both interventions reduced time-on-task.
The ICT intervention increased EdTech usage; both interventions reduced time-on-task.
Effects on student perceptions, attitudes (unstandardized)

Figure A20: ITT effects on student perceptions, attitudes


