# Explaining the Productivity Paradox

## Experimental Evidence from Educational Technology

RISE Annual Conference 2023

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de Barros, Andreas. (2023). Explaining the Productivity Paradox: Experimental Evidence from Educational Technology. (EdWorkingPaper: 23-853). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/mf5h-r010

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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.**

# 1/ 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?**

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Bettinger et al. (2022); Ma et al. (2020)

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)

# 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.

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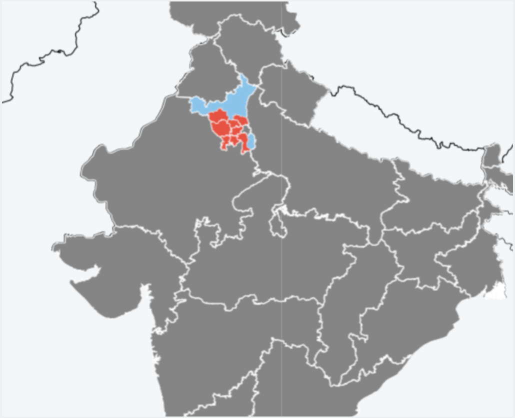
I find **negative effects** of the EdTech intervention on math, no effects on science learning, no effects of non-tech intervention, after 11 months.

- 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

# 2/ Context and intervention

# Our setting is the scale-up of a public-private partnership in Haryana's public secondary schools

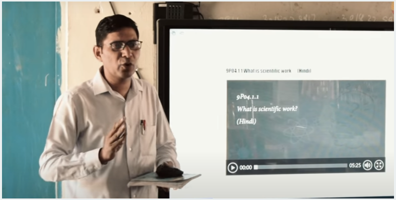
Figure 1: Location of the study



*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



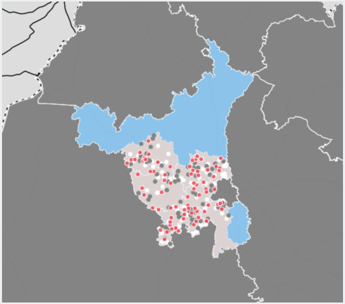

(a) Information and Communication Technology (ICT) infrastructure, video materials


(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).

▸ Sampling

# 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).
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- *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).

▸ 2PL IRT ▸ Distribution ▸ TIF

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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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- *Student attitudes towards mathematics, science:*
  Student survey

▸ *QUIP* ▸ Student survey

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# We estimate intent-to-treat effects with OLS regressions

$$Y_{isvr} = \alpha + \sum_{k=1}^{2} \beta_k T_{ksvr} + \boldsymbol{X}_{isvr} + \phi_r + \epsilon_{isvr} \tag{1}$$

- $\beta_k$ 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: $\boldsymbol{X}_{isvr}^{t=1}$ as covariates.
- $\boldsymbol{X}_{isvr}^{t=1}$: 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.

▸ Covariates

# 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.

▸ Balance

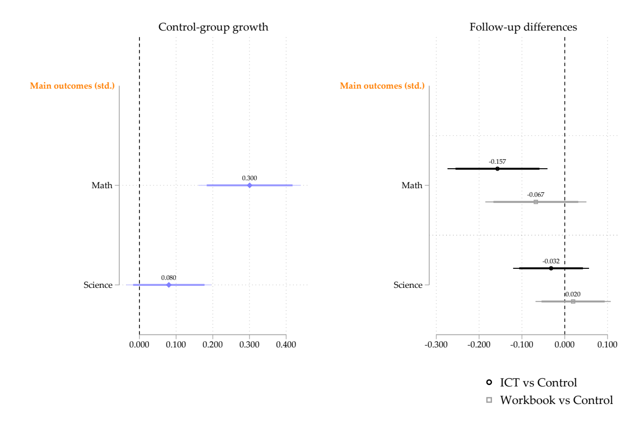
# Key components of the intervention were implemented as intended and taken up well

1. ICT infrastructure upgrades implemented as planned. ▸ Figure
2. Videos installed, used (slightly less in math). ▸ Figure
3. Workbooks distributed and used, outside the classroom. ▸ Figure
4. Limited use of in-class exercises, peer learning, in both groups. ▸ Figure
5. Limited on-site coaching (anecdotal).

# 4/ Results

# After 11 months of the ICT intervention, I find neg. effects on math, no effects on science test scores

Figure 4: Intent-to-treat (ITT) effects on student learning




*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. ▸ Figure
2. Grade-9 students and weaker students are affected *only slightly* more negatively (in math). ▸ Math ▸ Science
3. Math effects are *only slightly* larger for below-level material; otherwise uniform across domains. ▸ Figure

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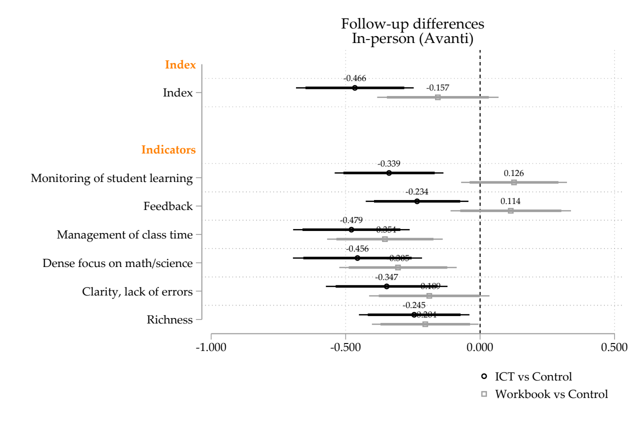
# I find negative effects of the ICT intervention on the quality of instruction students receive

Figure 5: ITT effects on instructional quality

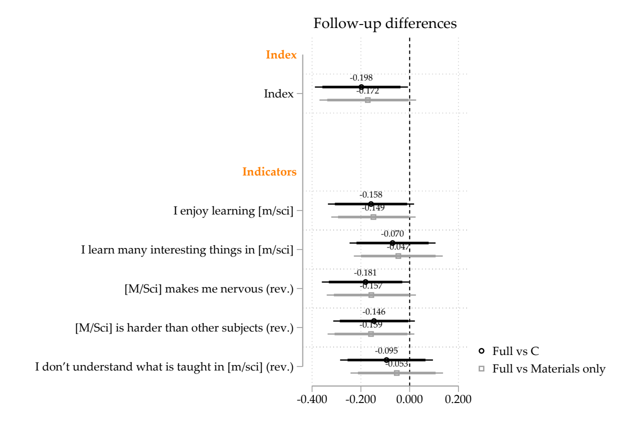



*Notes.* All estimations include randomization strata fixed effects and a vector of school- and village-level covariates, selected via LASSO. Horizontal bars show confidence intervals (s.e.s clustered at the school level).
*Sample.* 1,343 classroom observations in mathematics and science.

▸ Adjusted ▸ Practices (Stallings)

# 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.

▸ Unstd.

# 5/ Conclusion

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- I also observed negative effects on student attitudes for the non-tech intervention, suggesting *any* reform may explain at least part of the story.
- 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.

# 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.

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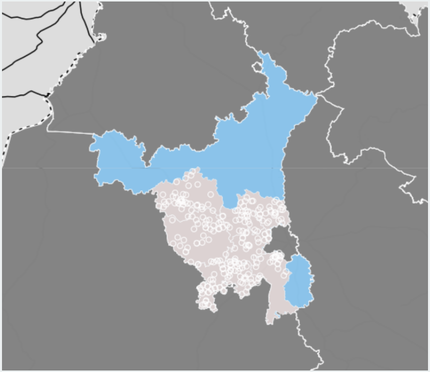
# Impact and next steps

- **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.

# 6/ Appendix

# We purposely sampled 240 secondary schools, following an infrastructure survey

Figure A1: Sample of 240 government senior secondary schools

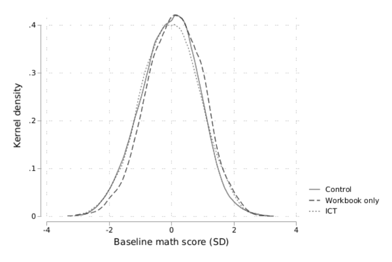


*Notes.* This figure depicts the 240 senior secondary government schools purposely selected for the study.

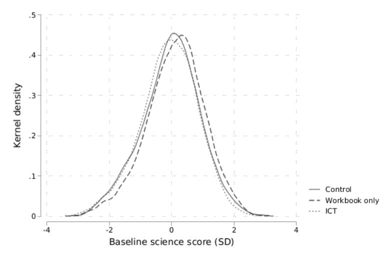
◂ Back

# The written tests do not suffer from ceiling or floor effects

Figure A2: Empirical distribution of test scores, by subject




(a) Mathematics




(b) Science

*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.

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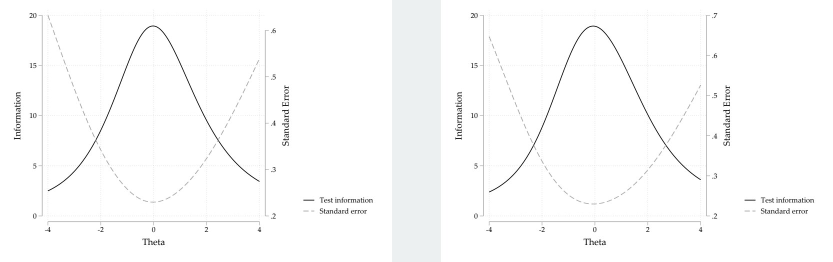
# The written tests measure with high levels of precision, across the ability distribution

Figure A3: Test information functions (TIFs)




(a) Mathematics

(b) Science

*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.

◂ Back

# 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 $b$.

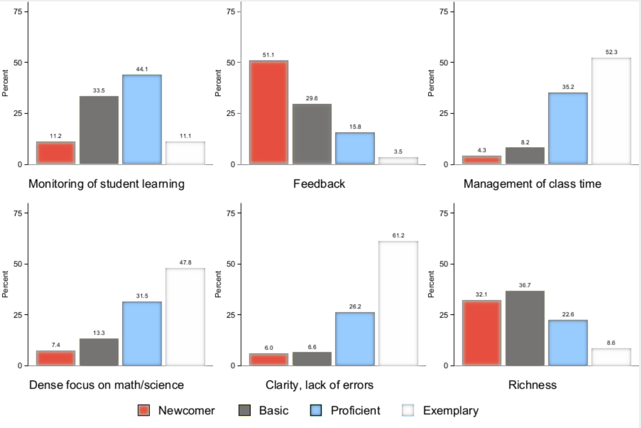
$$P_{ij}\left(\theta_j, b_i, a_i\right) = \frac{\exp\left[a_i\left(\theta_j - b_i\right)\right]}{1 + \exp\left[a_i\left(\theta_j - b_j\right)\right]} \tag{2}$$

- 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).

Back

# 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.

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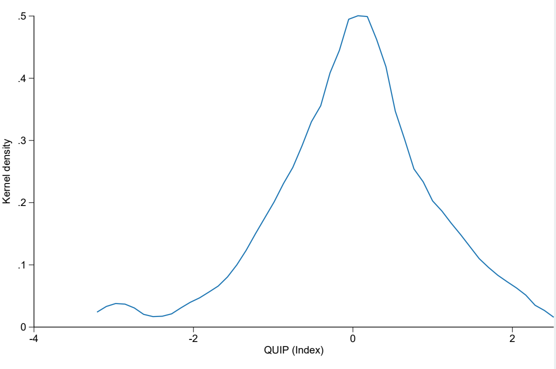
# We measure instructional behaviors, quality with the *QUIP* classroom observation instrument (ctd.)

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.

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# We measure student attitudes towards mathematics with one-on-one interviews

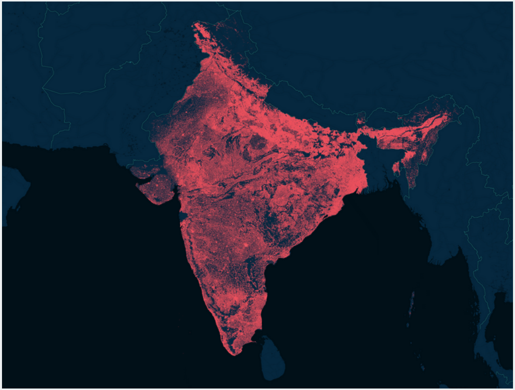
We calculate an inverse covariance matrix-weighted index, for the following items

- Student enjoys learning math
- Student finds math easy to understand
- Math makes the student nervous (reversed)
- Student finds math harder than other subjects (reversed)

Back

# Through GIS, we link India’s EMIS to village-level censuses and satellite-recorded nightlights data

Figure A6: India’s schools

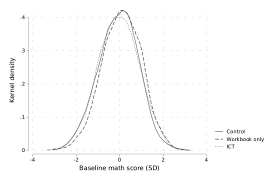


*Notes.* This figure shows all registered schools as per India’s education management information system (as of 2017), and their locations (as of 2020). Village-level census tracts are for 2011. Satellite data comes from SHRUG.

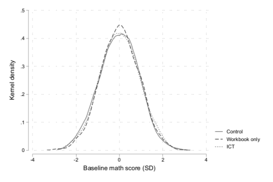
Back

# Results are robust to dropping the seven most severely imbalanced randomization triplets

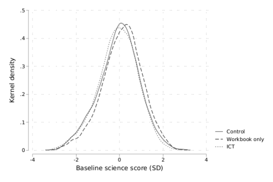
Figure A7: Balance on baseline test scores before/after dropping imbalanced strata.



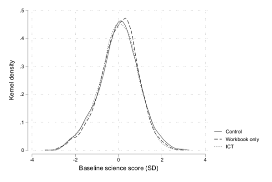

(a) Mathematics




(b) Math (adj.)




(c) Science




(d) Science (adj.)

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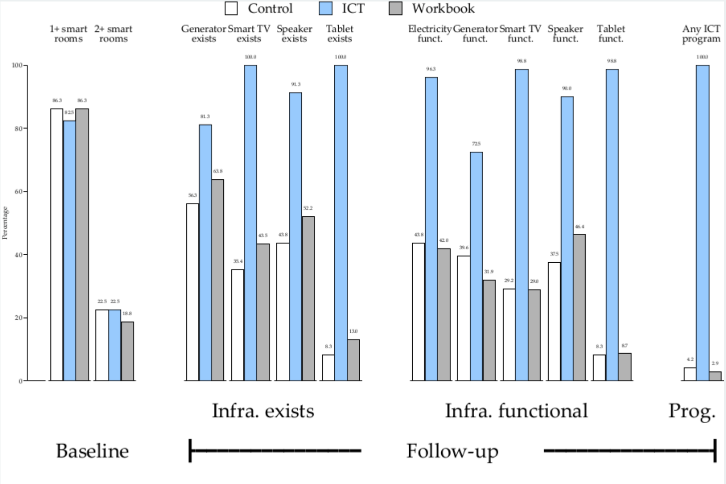
# ICT infrastructure installed and functional—the other schools do not have ICT programs

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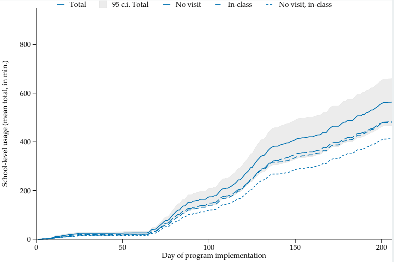
# Teachers use the video materials—including on days without school visits

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

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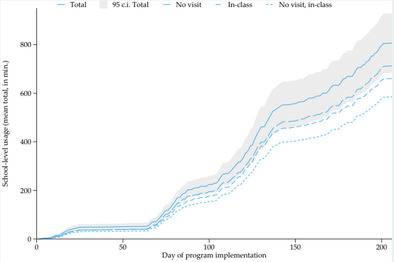


(b) Science

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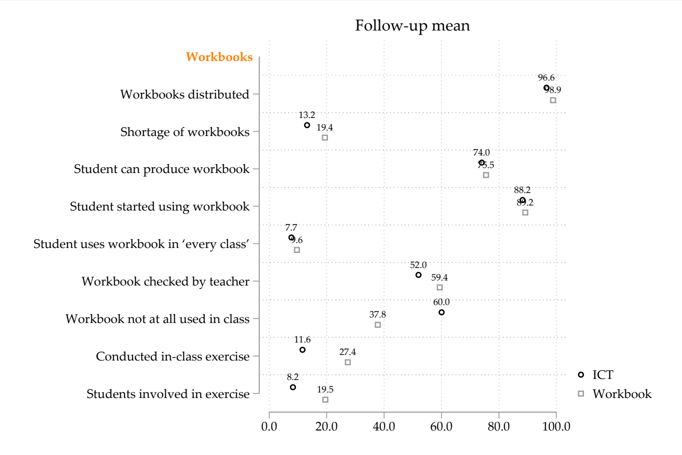
# Workbooks were distributed and they are used (outside the classroom)

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

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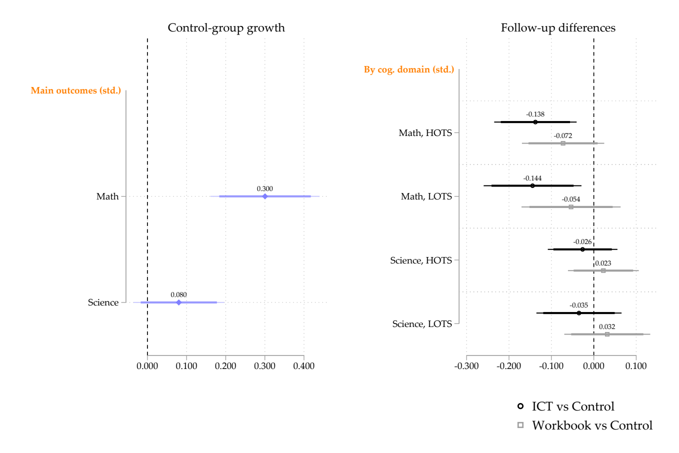
# Effects are similar across higher-order and lower-order skills

Figure A11: ITT effects on student learning by cognitive domain

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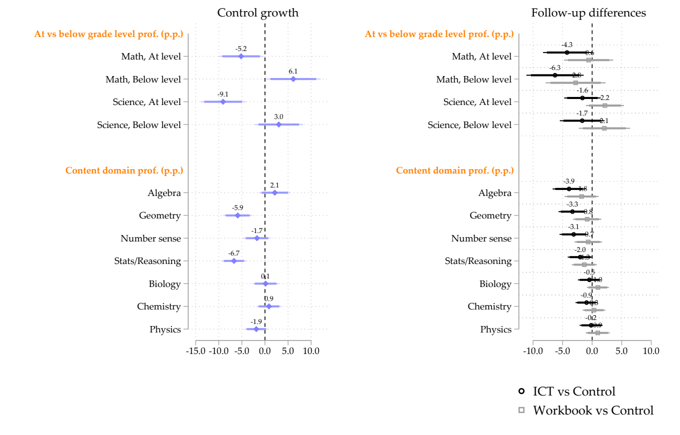
# Effects are similar across curricular grade-levels and across content domains

Figure A12: ITT effects on student learning by content domain

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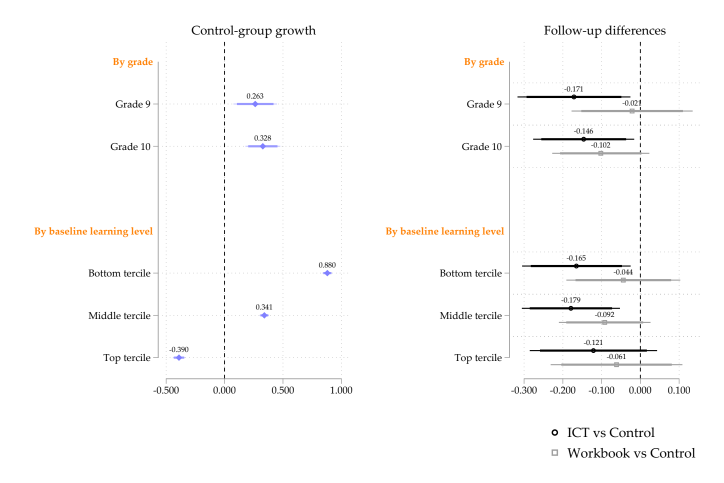
# Effects for student subgroups, in math

Figure A13: Heterogeneous ITT effects on math learning

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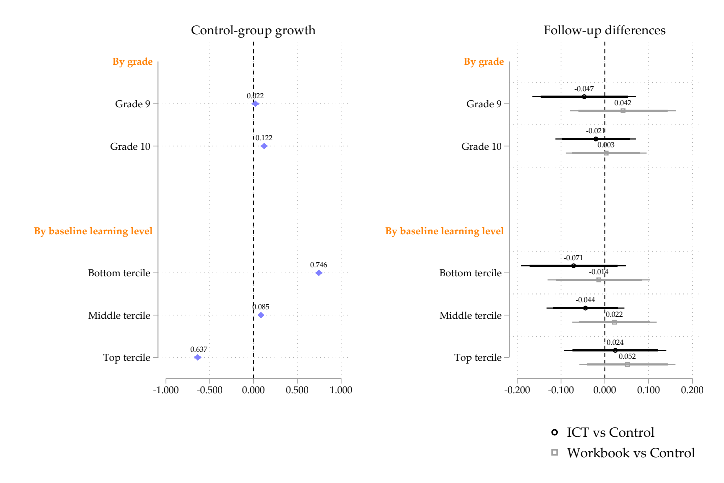
# Effects for student subgroups, in science

Figure A14: Heterogeneous ITT effects on science learning

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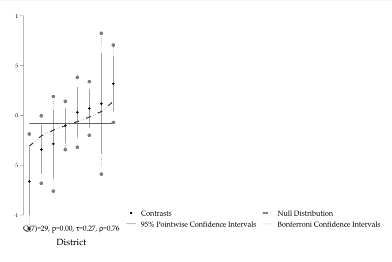
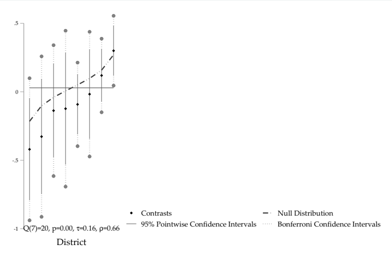
# Test scores: Effects by district, in math

Figure A15: Heterogeneous ITT effects on math learning




(a) ICT vs Control




(b) Workbook vs Control

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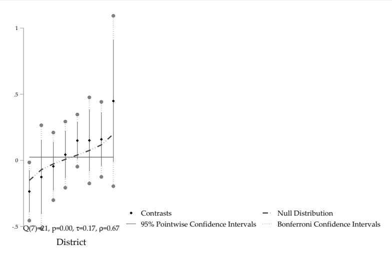
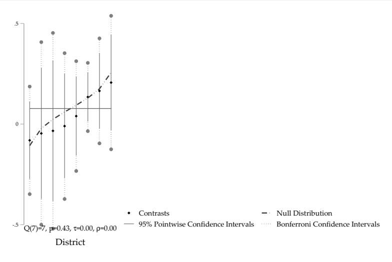
# Test scores: Effects by district, in science

Figure A16: Heterogeneous ITT effects on science learning




(a) ICT vs Control




(b) Workbook vs Control

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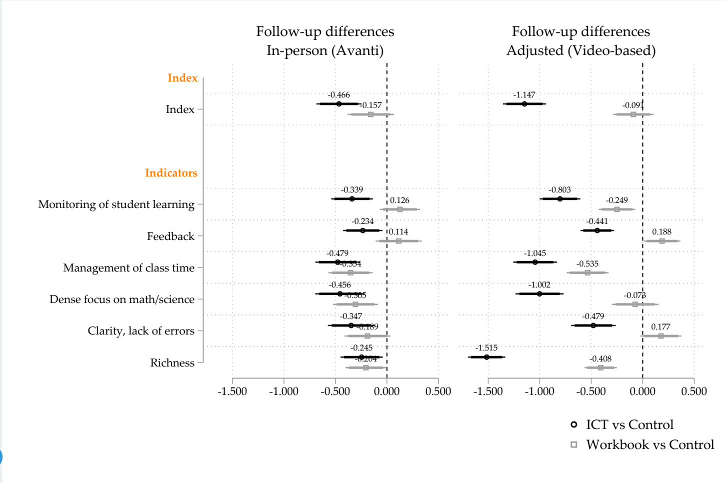
# NGO-administered ratings provide an upper bound for effects on instructional quality

Figure A17: ITT effects on instructional quality (adjusted)

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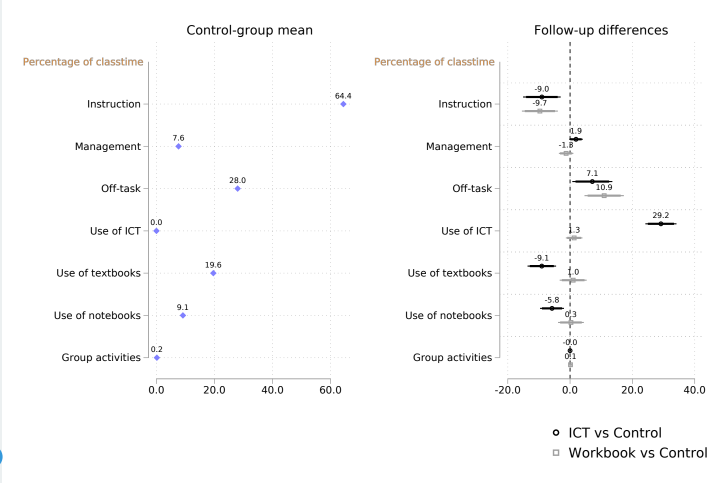
# The ICT intervention increased EdTech usage; both interventions reduced time-on-task

Figure A18: ITT effects on teaching behaviors

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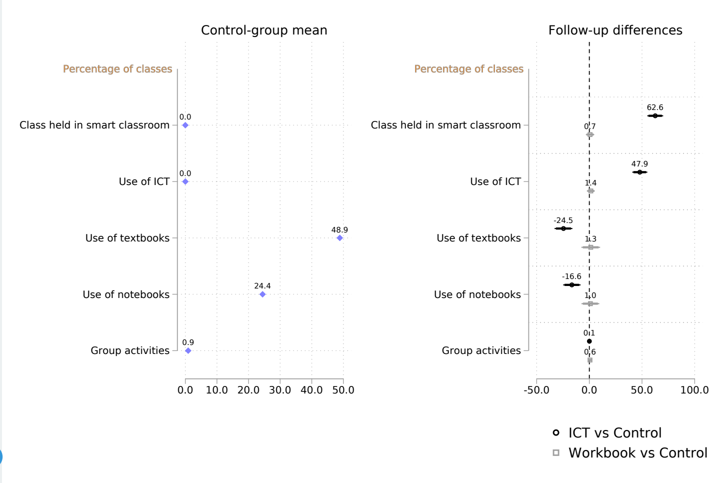
# The ICT intervention increased EdTech usage; both interventions reduced time-on-task

Figure A19: ITT effects on teaching behaviors

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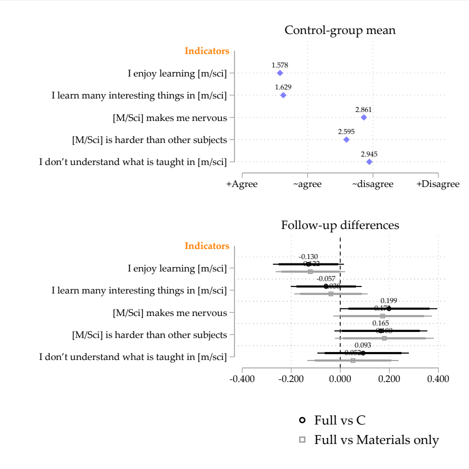
# Effects on student perceptions, attitudes (unstandardized)

Figure A20: ITT effects on student perceptions, attitudes

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