COVID-19 Learning loss and recovery: Panel data evidence from India

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Based on joint work with Karthik Muralidharan and Mauricio Romero

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Motivation

- COVID-19 disrupted education systems worldwide, **but shock more severe in LMICs**
  - LMICs had longer school closures (Agarwal, 2022; UNESCO, 2022)
  - Schools/parents in LMICs less equipped to pivot to remote instruction
  - LMICs more vulnerable to economic and health shocks (Patrinos, Vegas, & Carter-Rau, 2022)
  - May exacerbate 'learning crisis' and increase educational inequality (World Bank, 2020)
  - Lost lifetime earnings due to reduced human capital accumulation estimated at up to $\sim$\$17 trillion (World Bank, UNESCO and UNICEF, 2021)

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- India illustrates the severity of the COVID-19 shock in LMICs starkly
  - Most of the economy reopened much before schools did (schools were closed ∼ 18 months)
  - An estimated 3.2 million people died by Sept 2021 (Jha et al., 2022)
  - Severe household economic shocks, esp during lockdowns (Kesar et al., 2021)

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  - An estimated 3.2 million people died by Sept 2021 (Jha et al., 2022)
  - Severe household economic shocks, esp during lockdowns (Kesar et al., 2021)
- Substantial (justified) effort in understanding "learning loss"
  - Relatively little evidence (yet) on magnitudes (Pratham, 2021)
  - It is very unclear how persistent these losses are (or how quickly children converge)
  - Very little evidence on how to address system-wide losses *after schools have reopened*

This paper

- We provide new evidence for Tamil Nadu (pop. $\sim$77 million)
  - Large panel data set: household-based census across 220 villages, $\sim$19k children
  - Multiple rounds of in-person data collection (2019, Dec 2021, Feb 2022 and May 2022)
  - Near-representative of rural communities in the state

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- **Three main research questions**:
  - How large were "learning losses" at the end of school closures?
  - How much did children recover in the first six months of school re-opening?
  - How much of the recovery comes from a large-scale government remediation program?
- For each of these questions, we'll also look at inequality

Contributions to the literature

- COVID-19 learning losses in LMICs (Patrinos et al., 2022; Moscoviz & Evans, 2022)
  - Most estimates rely on simulations or phone-based testing in non-representative samples (except Hevia, Vergara-Lope, Velásquez-Durán, and Calderón (2022) in Mexico)

  ⇒ **In-person testing in a near-representative sample, IRT-linked measurement**

- Evidence on recovery

  ⇒ **Measure system-wide catch-up in LMICs**

  ⇒ Other studies? (Lichand & Doria, 2022)

- Evidence on mitigation/remediation
  - Several studies on remote tutoring and technology interventions *during* school closures (e.g., N. Angrist, Bergman, and Matsheng (2022); Carlana and La Ferrara (2021); Hassan, Islam, Siddique, and Wang (2021))

  ⇒ **Evidence on at-scale program to remediate learning losses upon school opening**

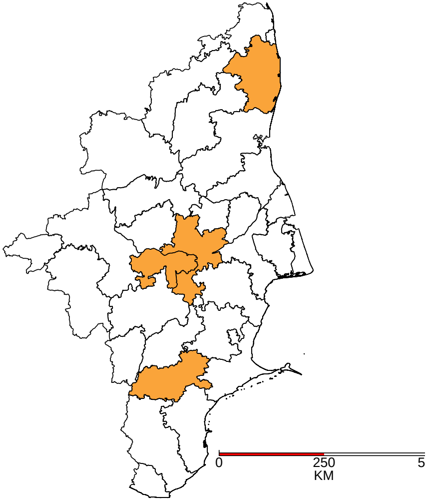
Learning loss (and recovery)

Learning loss (and recovery)

Setting

- In Jun-Aug of 2019: census of households with children < 8 yrs as the baseline for an RCT
  - 220 villages are spread across 4 districts in Tamil Nadu
  - 21,046 households
  - 25,126 children 2–7 years old tested in math and Tamil
  - Households resemble rural TN aggregates in state-wide representative data Comparison
- The experimental treatment was abandoned due to the COVID-19 pandemic
- Between Dec 2021 to May 2022, we went back to resurvey all the households
  - Tested all children 3–10 years old
  - 19,289 children aged 4–10 years for whom we have test scores in 2019 and 2021/22
  - Attrition does not vary by gender, SES, or baseline test scores Attrition

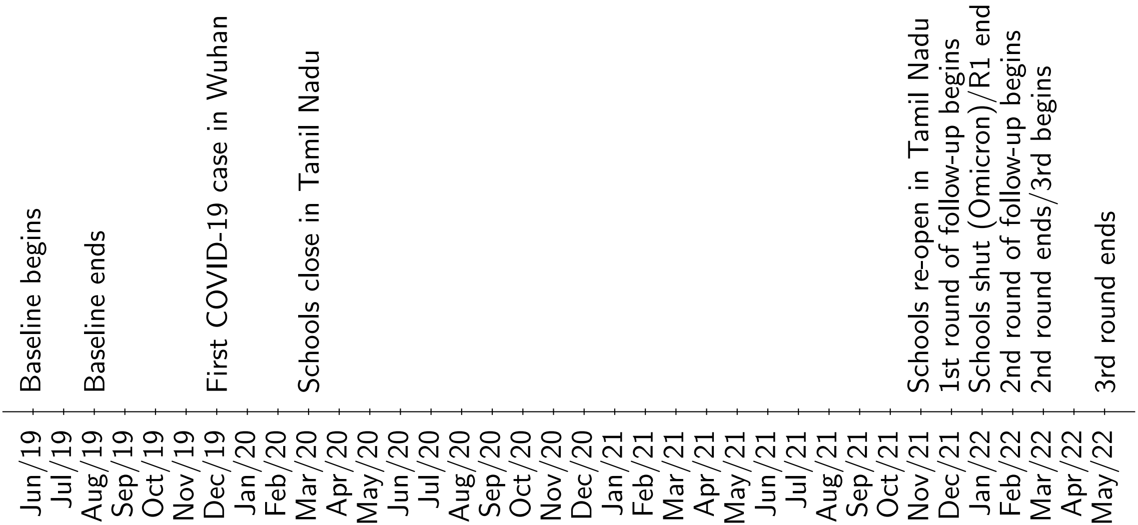
Map of sample districts in Tamil Nadu



Measurement Waves

- We randomized households into two groups within each village ‣ Balance
  - These were designated the "early" and "late" follow-up groups
  - The "early" group was (arbitrarily) split into two sub-groups due to the Omicron wave
  - Generates 2 rounds of student-level measurement, and 4 rounds of cohort-level mean scores
- Due to Omicron wave, follow-up data collection was done in 3 stages:
  1. **Early follow-up I**: Dec 20th, 2021 – Jan 7th,2022 (N=7,683)
  2. **Early follow-up II**: Feb 25 – March 23,2022 (N=5,616)
  3. **Late follow-up**: March 11 – May 7, 2022 (N=13,798)
- Variation between early and late follow-up is random (stratified within village)
- Variation within early group not randomized, but balanced on observables

Timeline


Baseline begins
Baseline ends
First COVID-19 case in Wuhan
Schools close in Tamil Nadu
Schools re-open in Tamil Nadu
1st round of follow-up begins
Schools shut (Omicron)/R1 end
2nd round of follow-up begins
2nd round ends/3rd begins
3rd round ends
Jun/19
Jul/19
Aug/19
Sep/19
Oct/19
Nov/19
Dec/19
Jan/20
Feb/20
Mar/20
Apr/20
May/20
Jun/20
Jul/20
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Jul/21
Aug/21
Sep/21
Oct/21
Nov/21
Dec/21
Jan/22
Feb/22
Mar/22
Apr/22
May/22

Difference in observed characteristics across rounds

	(1) Dec/21-Jan/22	(2) Feb/22-Mar/22	(3) Mar/22-May/22	(4) p-value (H_o: Equality)	(5) p-value (H_o: Equality within village)
Male	0.51	0.52	0.51	0.390	0.553
	(0.50)	(0.50)	(0.50)		
	[5,554]	[3,993]	[9,752]		
Mother Edu: $<$ Gr. 9	0.35	0.36	0.34	0.248	0.121
	(0.48)	(0.48)	(0.47)		
	[5,517]	[3,963]	[9,672]		
Mother Edu: Gr. 9-11	0.32	0.31	0.33	0.085*	0.097*
	(0.47)	(0.46)	(0.47)		
	[5,517]	[3,963]	[9,672]		
Mother Edu: Gr. 12+	0.33	0.34	0.33	0.861	0.486
	(0.47)	(0.47)	(0.47)		
	[5,517]	[3,963]	[9,672]		
SES Decile	4.99	4.85	4.97	0.383	0.563
	(2.79)	(2.92)	(2.84)		
	[5,554]	[3,993]	[9,752]		
Math (2019)	-0.01	0.01	0.00	0.842	0.725
	(1.10)	(1.11)	(1.08)		
	[5,554]	[3,993]	[9,752]		
Tamil (2019)	-0.00	0.01	0.00	0.964	0.908
	(0.64)	(0.65)	(0.64)		
	[5,554]	[3,993]	[9,752]		
Government school (2020-21)	0.51	0.51	0.50	0.653	0.493
	(0.50)	(0.50)	(0.50)		
	[5,312]	[3,989]	[9,751]		
Private school (2020-21)	0.29	0.29	0.27	0.225	0.281
	(0.45)	(0.45)	(0.45)		
	[5,312]	[3,989]	[9,751]		
Age at baseline (months)	55.87	56.13	55.76	0.594	0.293
	(19.35)	(19.45)	(19.54)		
	[5,554]	[3,993]	[9,752]		

Learning Assessments

- Our focus was on measuring foundational literacy and numeracy
  - In 2019, these covered simple competences (in keeping with a focus on kids aged 3-5)
  - In 2021, we broadened the range of skills to be able to measure ages 3-10

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- Tests are scored using Item Response Theory
  - Large overlap of items between rounds and ages
  - Tests are vertically linked across rounds and linked across ages
  - Test scores standardized with reference to 5-year-olds in 2019

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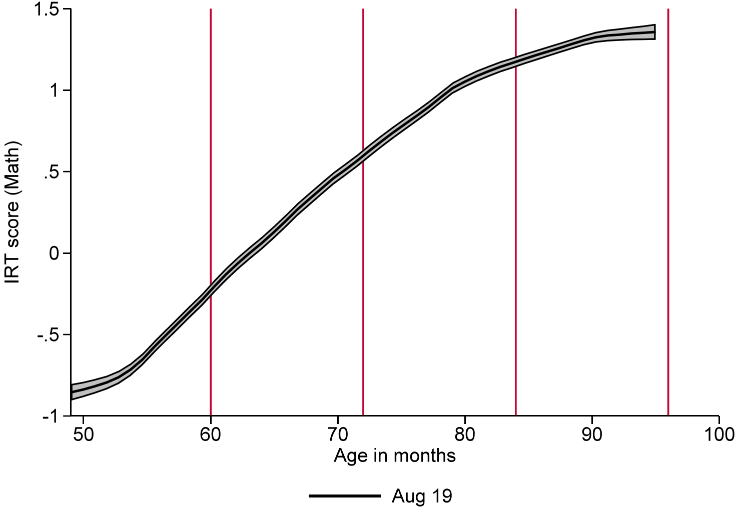
  - In 2021, we broadened the range of skills to be able to measure ages 3-10
- Tests are scored using Item Response Theory
  - Large overlap of items between rounds and ages
  - Tests are vertically linked across rounds and linked across ages
  - Test scores standardized with reference to 5-year-olds in 2019
- Tests are typically well-distributed (esp in 2021/22)
  - In 2019, problems of floor/ceiling effects at ends of age distribution
  - Fixed in 2021, with a broader range of items
  - No results are sensitive to this

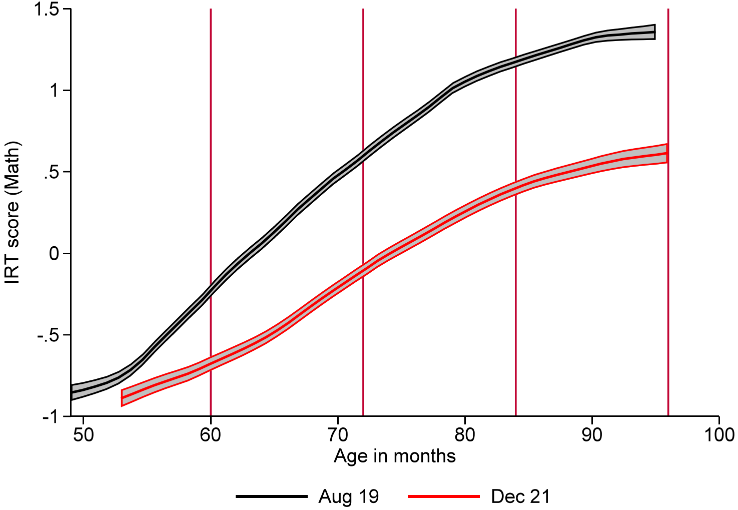
Learning loss (and recovery)

Learning profile in math in 2019



Large drop in age-adjusted achievement in Dec 2021

...which is a change in *gradient*



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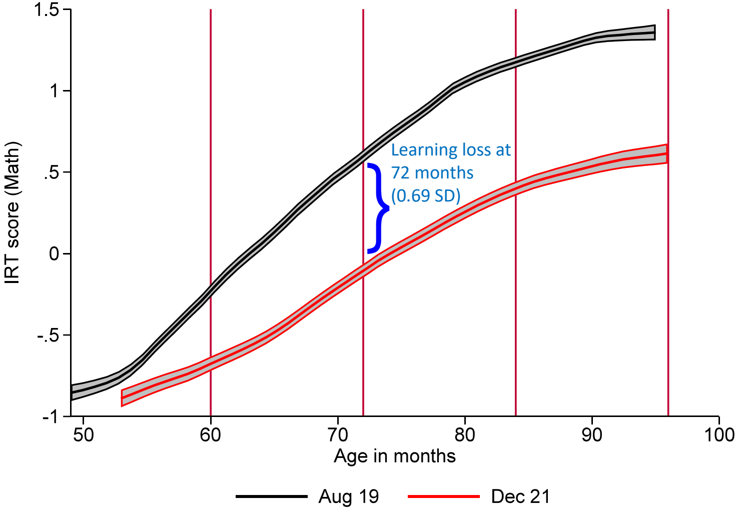

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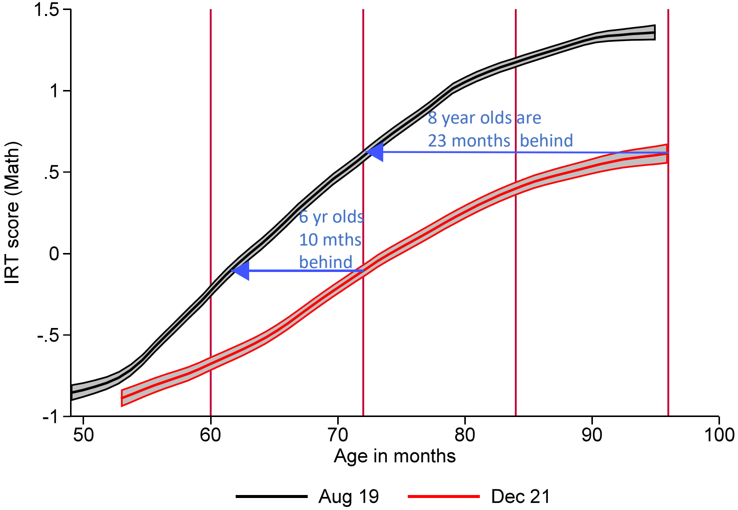
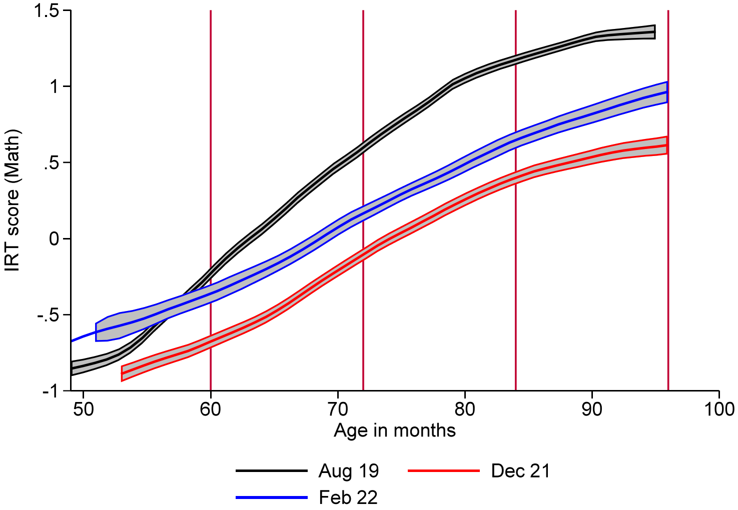
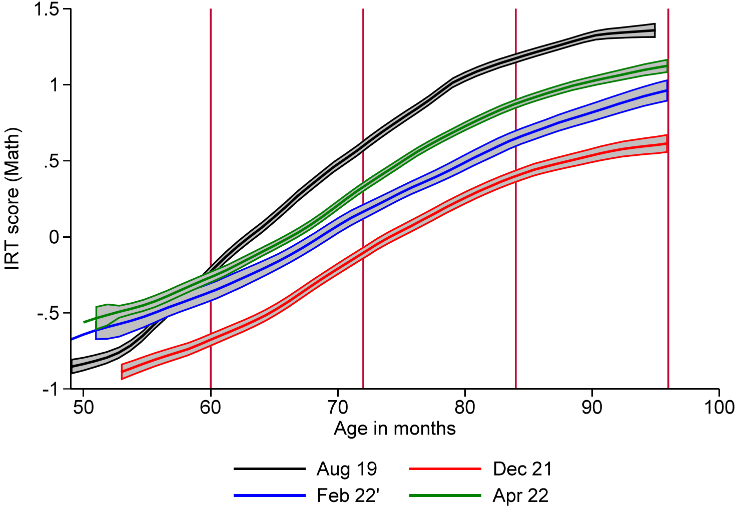


But this gap is smaller by Feb 2022

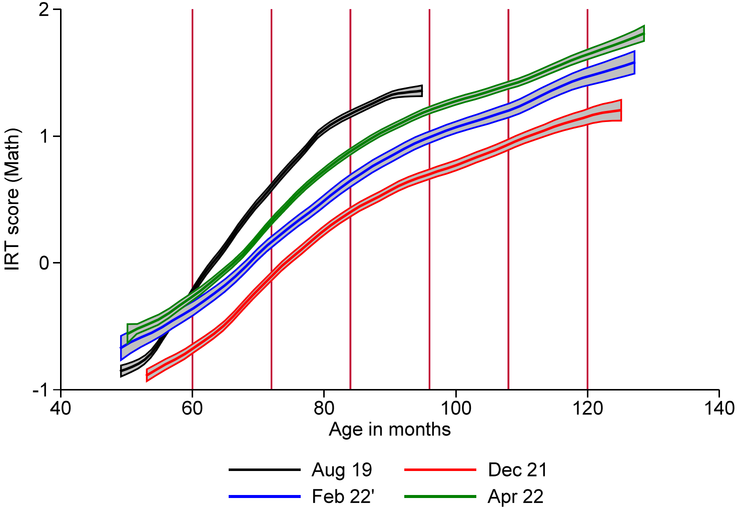


Rapid recovery: 2/3 of the initial gap gone by April '22

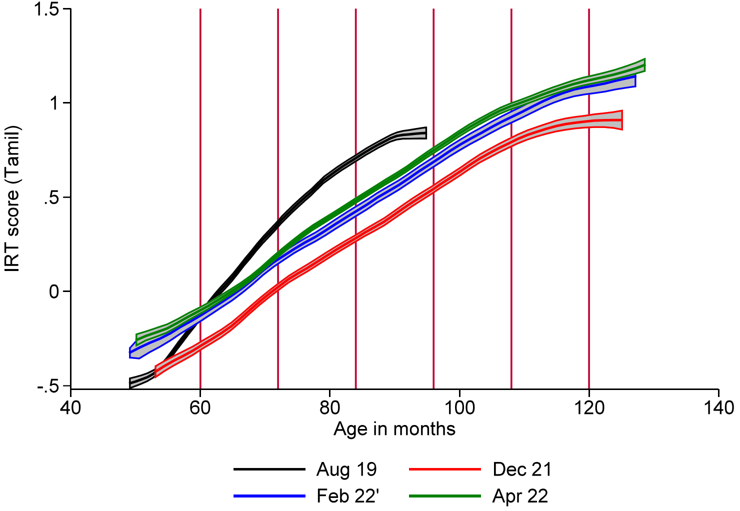


Catch-up seems as rapid in later primary school

At ages 8-10 (where we don't have a baseline)



Rapid recovery also in language (with smaller initial losses)



Learning loss at different ages

Table: Learning loss between August 2019 and December 2021

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Learning loss at different ages								
	Math				Tamil			
Age (in months)	60	72	84	96	60	72	84	96
IRT score (Aug 2019)	-0.61	0.23	0.80	1.02	-0.14	0.34	0.68	0.84
IRT score (Dec 2021)	-1.04	-0.46	0.06	0.28	-0.29	0.02	0.28	0.42
Absolute loss (in SD)	0.43	0.69	0.74	0.75	0.15	0.32	0.40	0.41
Developmental lag (in months)	10.0	10.0	14.5	23.5	5.5	8.0	13.5	21.5

Notes: Panel A presents, for children of different ages, the raw IRT score in wave 0 (Aug 2019) and wave 1 (Dec 2021), as well as the difference between the two (the absolute learning loss in standard deviations), and the developmental lag (i.e., how much longer, in months, it took a student in 2021 to achieve the same score as a student in 2019).

Heterogeneity in learning loss

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Math score (in SD)				Tamil score (in SD)			
Wave 1 (Dec 2021)	-.73***	-.74***	-.76***	-.75***	-.35***	-.35***	-.37***	-.38***
	(.031)	(.038)	(.042)	(.049)	(.02)	(.023)	(.027)	(.029)
Male × Dec 21		.023				-.0074		
		(.041)				(.022)		
Mother Edu: Gr. 9-11 × Dec 21			.019				.0015	
			(.053)				(.03)	
Mother Edu: Gr. 12+ × Dec 21			.09*				.06**	
			(.049)				(.025)	
SES Decile × Dec 21				.0046				.0061
				(.0075)				(.0039)
N. of obs.	13,083	13,083	13,083	13,083	13,083	13,083	13,083	13,083
R-squared	.33	.33	.33	.33	.31	.31	.31	.31

Note: This table compares Wave 0 (Aug 2019) to Wave 1 (Dec 2021). Village FE included in all regressions. Standard errors clustered at village level.

Recovery from learning loss

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Recovery at different ages								
	Math				Tamil			
Age (in months)	60	72	84	96	60	72	84	96
IRT score (Aug 2019)	-0.61	0.23	0.80	1.02	-0.14	0.34	0.68	0.84
IRT score (Dec 2021)	-1.04	-0.46	0.06	0.28	-0.29	0.02	0.28	0.42
IRT score (Feb 2022)	-0.72	-0.18	0.31	0.66	-0.13	0.17	0.42	0.69
IRT score (Apr 2022)	-0.62	-0.02	0.55	0.88	-0.10	0.20	0.48	0.75
Absolute loss (in SD)	0.43	0.69	0.74	0.75	0.15	0.32	0.40	0.41
Absolute recovery (in SD) by Feb 22	0.32	0.28	0.26	0.38	0.16	0.15	0.14	0.26
Absolute recovery (in SD) by Apr 22	0.42	0.44	0.49	0.60	0.19	0.17	0.20	0.32

Notes: Panel A presents, for children of different ages, the raw IRT score in wave 0 (Aug 2019) and three survey waves in 2021-22. The difference between the Aug '19 and Dec '21 waves measures absolute learning loss. The difference between Dec '21 and the subsequent rounds measures recovery.

Heterogeneity in recovery from learning loss

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Math score (in SD)				Tamil score (in SD)			
Wave 2 (Feb 2022)	.24***	.27***	.23***	.26***	.12***	.11***	.12***	.14***
	(.043)	(.047)	(.056)	(.061)	(.024)	(.026)	(.031)	(.031)
Wave 3 (April 2022)	.46***	.48***	.48***	.55***	.19***	.19***	.2***	.23***
	(.025)	(.03)	(.037)	(.043)	(.013)	(.016)	(.02)	(.021)
Interactions:								
Male × Feb 22		-.068				.023		
		(.045)				(.023)		
Male × Apr 22		-.044				-.0024		
		(.033)				(.017)		
Mother Edu: Gr. 9-11 × Feb 22			.027				.0047	
			(.057)				(.029)	
Mother Edu: Gr. 9-11 × Apr 22			.068				.023	
			(.047)				(.025)	
Mother Edu: Gr. 12+ × Feb 22			-.014				-.023	
			(.061)				(.031)	
Mother Edu: Gr. 12+ × Apr 22			-.13***				-.061**	
			(.043)				(.024)	
SES Decile × Feb 22				-.0055				-.0045
				(.0089)				(.0042)
SES Decile × Apr 22				-.017**				-.008**
				(.0069)				(.0034)
N. of obs.	18,978	18,978	18,978	18,978	18,978	18,978	18,978	18,978
R-squared	.4	.4	.4	.4	.46	.46	.46	.46

Note: This table compares Wave 1 (Dec 2021) to Waves 2 (Feb 2022) and 3 (April 2022). Village FE included in all regressions. Standard errors clustered at village level.

Is recovery an artifact of what/how we test?

- **Does recovery reflect the material being tested?**
  - Tests are not linked to syllabus
  - Content largely about foundational literacy and numeracy
  - Esp. in 2021-22, these tests are designed with broad coverage
- **Does recovery reflect mode of administration?**
  - Tests are administered at home in a 1:1 setting
  - Not just mechanically caused by, e.g., greater familiarity with writing
- **Does recovery reflect other failures in testing or linking?**
  - Very similar patterns when looking at individual items and percent correct
  - Ceiling/floor effects not an issue in the 2021/22 rounds

How should we think about catch-up?

- The recovery likely a result of many factors
  - "Natural" recovery as students return to school
  - Compensatory actions taken at school or by households
  - **State Government started a large supplementary instruction program for recovery**

Learning loss (and recovery)

Massive state-wide after-school remedial campaign

Ilam Thedi Kalvi ("Education at doorstep")

- The state government's main initiative is called Ilam Thedi Kalvi (ITK)
    - Started in Nov 2021, extended broadly in January 2022
    - 60-90 minutes of supplementary lessons
    - Delivered by cadre of volunteers (more than 200,000 in the state)
    - Stipend of INR 1,000/month ($\sim$ 12 USD) — vs. INR 28,660/month for primary teachers
    - Held in various spaces (schools, AWCs, volunteer house)
    - Special curriculum developed to remedy learning loss
    - Very salient in the state

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  - Held in various spaces (schools, AWCs, volunteer house)
  - Special curriculum developed to remedy learning loss
  - Very salient in the state
- Similar to Banerjee et al. (2017) and Duflo et al. (2020)
- In the last survey wave (April-May wave), we elicit extensive questions about ITK

Households know about ITK

And report their children attend

- 91% of households have heard about ITK
- 57% of HH report children attend ITK
- Of those attending, 92% HH report ≥ 4 days per week attendance
- Attendance rates are higher among poorer households
  - Most likely reflects implementation led by government schools
  - Could also reflect lack of alternative means to support recovery

ITK participation was progressive

	(1) Does not attend ITK	(2) Attend ITK	(3) Difference (overall)	(4) Difference (village FE)
Male	0.52	0.49	-0.03***	-0.03**
	(0.50)	(0.50)	(0.01)	(0.01)
	[3,832]	[5,145]	[8,977]	[8,977]
Age in months	86.64	93.70	7.07***	8.03***
	(19.14)	(17.57)	(0.46)	(0.50)
	[3,832]	[5,145]	[8,977]	[8,977]
Mother Edu: Up to Gr. 8	0.29	0.39	0.10***	0.09***
	(0.45)	(0.49)	(0.02)	(0.01)
	[3,806]	[5,096]	[8,902]	[8,902]
Mother Edu: Gr. 9-11	0.31	0.35	0.04***	0.03**
	(0.46)	(0.48)	(0.01)	(0.01)
	[3,806]	[5,096]	[8,902]	[8,902]
Mother Edu: Gr. 12+	0.39	0.26	-0.13***	-0.13***
	(0.49)	(0.44)	(0.02)	(0.01)
	[3,806]	[5,096]	[8,902]	[8,902]
SES Decile	5.42	4.59	-0.84***	-0.77***
	(2.91)	(2.73)	(0.10)	(0.09)
	[3,832]	[5,145]	[8,977]	[8,977]
Math (2019)	0.08	-0.04	-0.12***	-0.11***
	(1.12)	(1.09)	(0.03)	(0.03)
	[3,832]	[5,145]	[8,977]	[8,977]
Tamil (2019)	0.04	-0.02	-0.06***	-0.06***
	(0.65)	(0.65)	(0.02)	(0.02)
	[3,832]	[5,145]	[8,977]	[8,977]

ITK participation was concentrated among government school students

	(1) Does not attend ITK	(2) Attend ITK	(3) Difference (overall)	(4) Difference (village FE)
Government school (2021-22)	0.42	0.90	0.48***	0.47***
	(0.49)	(0.30)	(0.02)	(0.02)
	[3,832]	[5,145]	[8,977]	[8,977]
Private school (2021-22)	0.47	0.08	-0.39***	-0.35***
	(0.50)	(0.27)	(0.02)	(0.02)
	[3,832]	[5,145]	[8,977]	[8,977]
Anganwadi centre (2021-22)	0.10	0.02	-0.08***	-0.10***
	(0.30)	(0.13)	(0.01)	(0.01)
	[3,832]	[5,145]	[8,977]	[8,977]

- Program messaging and recruitment were all through the government machinery

ITK participants received fewer inputs to cope during COVID-19 school closures

	(1) Does not attend ITK	(2) Attend ITK	(3) Difference (overall)	(4) Difference (village FE)
Video classes	0.23	0.06	-0.17***	-0.15***
	(0.42)	(0.24)	(0.01)	(0.01)
Audio classes	0.09	0.06	-0.03***	-0.02***
	(0.29)	(0.24)	(0.01)	(0.01)
In-person classes	0.04	0.09	0.06***	0.06***
	(0.19)	(0.29)	(0.01)	(0.01)
School sent homework	0.37	0.27	-0.10***	-0.07***
	(0.48)	(0.44)	(0.02)	(0.01)
HH member teaches child	0.86	0.87	0.01	0.01
	(0.34)	(0.33)	(0.01)	(0.01)
Private tutoring	0.14	0.10	-0.04***	-0.01
	(0.35)	(0.30)	(0.01)	(0.01)

- Also lower use of internet, smartphones, books at home etc.

Evaluating the causal effect of ITK

- ITK participants seem negatively selected in the population
- We use "value-added" models (VAM) which control for baseline scores, demographics, enrollment type (determined before program rollout) and village FE
  - These rely on conditional ignorability for identification

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- Even without exogenous variation, estimates likely to approximate causal effect
  - VAM typically yield similar estimates as RCTs, RD, DiD, substantial predictive validity
    - School effects (Andrabi et al., 2011; Deming, 2014; Singh, 2015; J. D. Angrist et al., 2017; Singh, 2020; J. Angrist et al., 2021)
    - Teacher effects (Chetty et al., 2014; Bacher-Hicks et al., 2014; Bau & Das, 2020)

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    - Teacher effects (Chetty et al., 2014; Bacher-Hicks et al., 2014; Bau & Das, 2020)
- We will further control for extensive direct inputs as well, a la Chetty et al (2014)
- Estimate Oster (2019) bounds

Evaluating the causal effect of ITK

$$Y_{it} = \alpha_v + \beta.AttendITK_{it} + \gamma.\mathbf{X_i} + \phi.\mathbf{Y_{i,t-1}} + \epsilon_{it} \tag{1}$$

- Y_{it}: achievement in 2022
- $AttendITK_{it}$: indicator for whether child i attends an ITK center
- α_v: vector of village-level dummy variables
- $\mathbf{X_i}$: background characteristics (age, gender, SES, maternal education, and enrollment)
- $\mathbf{Y_{i,t-1}}$: lagged achievement measures in math and Tamil in 2019
- ϵ_{it}: error term

Assessing effect of *Illam Thedi Kalvi (ITK)* on math test scores

	Naive	VAM	Augmented
ITK effect			
N. of obs.			
R-squared			

Assessing effect of *Illam Thedi Kalvi (ITK)* on math test scores

	(1)		
	Naive	VAM	Augmented
ITK effect	.08***		
	(.027)		
N. of obs.	8,966		
R-squared	.32		

Assessing effect of *Illam Thedi Kalvi (ITK)* on math test scores

	(1)	(2)	
	Naive	VAM	Augmented
ITK effect	.08***	.17***	
	(.027)	(.026)	
N. of obs.	8,966	8,902	
R-squared	.32	.38	

Assessing effect of *Illam Thedi Kalvi (ITK)* on math test scores

	(1)	(2)	(3)
	Naive	VAM	Augmented
ITK effect	.08***	.17***	.16***
	(.027)	(.026)	(.026)
N. of obs.	8,966	8,902	8,901
R-squared	.32	.38	.39

Assessing effect of *Illam Thedi Kalvi (ITK)* on math test scores

	(1)	(2)	(3)	(4)
	Naive	VAM	Augmented	
ITK effect	.08***	.17***	.16***	.17***
	(.027)	(.026)	(.026)	(.025)
N. of obs.	8,966	8,902	8,901	8,901
R-squared	.32	.38	.39	.39

Assessing effect of *Illam Thedi Kalvi (ITK)* on math test scores

	(1)	(2)	(3)	(4)	(5)
	Naive	VAM	Augmented		
ITK effect	.08***	.17***	.16***	.17***	.16***
	(.027)	(.026)	(.026)	(.025)	(.025)
N. of obs.	8,966	8,902	8,901	8,901	8,901
R-squared	.32	.38	.39	.39	.39

▸ Full table

Assessing effect of *Illam Thedi Kalvi (ITK)* on Tamil test scores

	(1)	(2)	(3)	(4)	(5)
	Naive	VAM	Augmented		
ITK effect	.073***	.093***	.09***	.092***	.083***
	(.015)	(.015)	(.015)	(.015)	(.014)
N. of obs.	8,966	8,902	8,901	8,901	8,901
R-squared	.4	.45	.45	.46	.46

Full table

Oster bounds

- Sensitivity of our results to further omitted variables bias (Oster, 2019)
  - Assume that selection-on-unobservables equals selection on observed variables
  - Note; given negative selection into ITK, this will raise effect sizes
  - We'll treat age and village FE as orthogonal (base specifications)
  - Keep in mind: even the rich vector of inputs raises R^2 by 0.01

Sensitivity of Math *Illam Thedi Kalvi (ITK)* estimates to omitted variables bias

$R^2_{max} =$	$\tilde{R}^2 + 0.1(\tilde{R}^2 - \mathring{R}^2)$ (1)	$\tilde{R}^2 + 0.3(\tilde{R}^2 - \mathring{R}^2)$ (2)	$\tilde{R}^2 + 0.5(\tilde{R}^2 - \mathring{R}^2)$ (3)	$\tilde{R}^2 + 0.7(\tilde{R}^2 - \mathring{R}^2)$ (4)
Panel A: Math				
β^*	0.174	0.198	0.224	0.254
$\mathring{\beta}$	0.083	0.083	0.083	0.083
$\tilde{\beta}$	0.164	0.164	0.164	0.164
$\mathring{R}^2$	0.314	0.314	0.314	0.314
$\tilde{R}^2$	0.386	0.386	0.386	0.386

Sensitivity of Tamil *Illam Thedi Kalvi (ITK)* estimates to omitted variables bias

$R^2_{max} =$	$\tilde{R}^2 + 0.1(\tilde{R}^2 - \mathring{R}^2)$	$\tilde{R}^2 + 0.3(\tilde{R}^2 - \mathring{R}^2)$	$\tilde{R}^2 + 0.5(\tilde{R}^2 - \mathring{R}^2)$	$\tilde{R}^2 + 0.7(\tilde{R}^2 - \mathring{R}^2)$
	(1)	(2)	(3)	(4)
Panel B: Tamil				
β^*	0.095	0.100	0.105	0.112
$\mathring{\beta}$	0.076	0.076	0.076	0.076
$\tilde{\beta}$	0.093	0.093	0.093	0.093
$\mathring{R}^2$	0.400	0.400	0.400	0.400
$\tilde{R}^2$	0.451	0.451	0.451	0.451

ITK appears to contribute to the progressivity of cohort-level learning recovery

	Math				Tamil			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
If child attends ITK	.21***	.19***	.19***	.31***	.17***	.11***	.093***	.11***
.11*	.17***							
	(.041)	(.049)	(.032)	(.11)	(.026)	(.022)	(.028)	(.018)
(.06)	(.026)							
Interactions:								
ITK × Mother Edu: Gr. 9-11	-.021					-.015		
	(.057)					(.029)		
ITK × Mother Edu: Gr. 12+	-.1*					-.048		
	(.054)					(.032)		
ITK × SES Decile		-.0033					-.000019	
		(.008)					(.0043)	
ITK × Male			-.04					-.036
			(.038)					(.022)
ITK × Age				-.0015				

Estimating the contribution of ITK to recovery from learning losses

- ITK effect of 0.17 standard deviations in Math (for participants)
  - Compared to a learning loss of 0.67 SD in December 2021
  - Compared to a recovery of 0.45 SD between Dec 2021 - May 2022
  - Contribution to cohort-level catch up is 0.097 SD (0.17 $\times$ 57% take up)
  - $\sim$ 20% of the *population-level* catch-up
- ITK effect of 0.093 standard deviations in Tamil (for participants)
  - Compared to a learning loss of 0.33 SD in December 2021
  - Compared to a recovery of 0.19 SD between Dec 2021 and May 2022
  - Contribution to cohort-level catch up is 0.053 SD (0.093 $\times$ 57% take up)
  - $\sim$ 28% of the *population-level* catch-up
- $\sim$ 50% of the *population-level* learning loss would have been made up even without ITK

Learning loss (and recovery)

What can we take away from this?

- The worry about substantial learning losses is not misplaced
  - **Huge learning losses** at the point of school re-openings (Dec '2021)
- However, these losses do not have to be permanent
  - Fast recovery — 2/3 of gap closed in 4 months!
  - Reopening schools accounted for $\sim 50\%$ recovery
  - Supplemental remedial instruction can accelerate recovery and compensate regressive losses
- **Understanding effects of COVID-19 on education will need long-term follow-ups**
  - Current estimates of learning loss only partially informative
- **Caution:** Fast recovery might not be a "structural" feature
  - See e.g. Andrabi, Daniels, and Das (2021) on the Pakistan 2005 earthquake
  - Recovery likely reflects pandemic response policies and behavior
  - Recovery may well be slower elsewhere (or absent!)

Learning loss (and recovery)

Mindspark in COVID-19

Digital Divide and using EdTech at home

- Since 2015, we had been engaged in research on computer-aided instruction for learning
  - We evaluated a personalized CAI software called *Mindspark*
  - We found huge gains from this model in after-school centres in Delhi (Muralidharan, Singh, & Ganimian, 2019)
  - We implemented a three-year trial in Rajasthan, implementing it in government schools, also with large effects (Muralidharan and Singh, 2023)
- The Rajasthan trial ended in Feb 2020, fieldwork ending shortly before lockdowns
  - Schools were closed for 18 months
  - EdTech suddenly rocketed in prominence
  - Substantial concerns of learning loss, inequality
- Two key questions, relevant long after pandemic:
  - Can EdTech use at home stem learning loss and aid recovery?
  - How should we solve the Digital Divide?

Intervention design

Romero, Singh and Muralidharan (2023)

We set up an multi-arm RCT in Tamil Nadu

- **Treatment 1**: Provide households with *access* to Mindspark for smartphones/tablets:
  - Mimics a typical pandemic period intervention
  - Provides access to online learning material but no hardware
- **Treatment 2**: Provide some households with a dedicated internet-enabled tablet for accessing Mindspark
  - Aimed to solve the “Digital Divide” in access to hardware

Experiment design

Romero, Singh and Muralidharan (2023)

- Sample of 220 villages in four districts of Tamil Nadu
  - We had conducted a census of all children between 2-7 years of age in these villages in 2019
  - The experiment is restricted to households with students aged between 6-7 years old in 2019
- We randomize these groups into the following groups
  - **Tablet villages**: In 45 villages, offer all households with a 6-7 y.o. at baseline a tablet and Mindspark login
    - 43% take-up (many hh couldn't be reached, others declined)
    - The tablet was a loan to be collected back in June 2022
  - **App login villages**: In 89 of the remaining villages, we individually randomized half of 1026 households
- Both treatments were delivered in Oct 2021
- Data collection in Dec 2021, Feb 2022, April 2022

Big picture results

Romero, Singh and Muralidharan (2023)

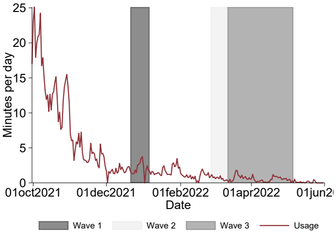
- **Does default provision of EdTech options work?**
  - It does not, even with a validated product
  - Almost nobody took up the treatment (12/556 households)
- **Did tablet provision work?**
  - Well, also not really...
  - Usage started out pretty high, sharply tapered down
  - Asymptoted close to zero after 30 days
  - Children kept using other apps, some evidence of **negative** cognitive effects by April-May!
- **These interventions mimic default EdTech policies in multiple states**

Usage over time in the tablets group

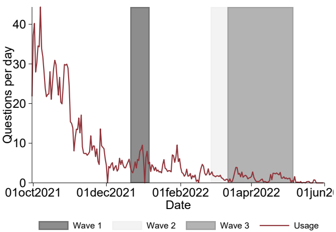
Romero, Singh and Muralidharan (2023)

Figure: Mindspark usage and data collection activities for the tablet treatment

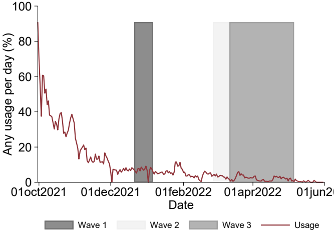
(a) Minutes in the app



(b) Questions per day



(c) Any usage per day



Note: This figure presents the evolution of Mindspark usage by calendar date, as well as the dates of data collection activities (shaded).

Pulling this together
General principles

- Complementarity between technology and supervision
- Implementation matters
- Usage matters – and is easily tracked
- Much of what EdTech money is being spent on will not translate into learning gains

Thank you

- Questions? Thoughts? Comments?

- Please reach out: abhijeet.singh@hhs.se

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Comparing TN ECE Baseline sample to NFHS - Household characteristics

	(1) NFHS-V sample	(2) Baseline sample	(3) Difference
Panel A: Assets			
Internet	0.59	0.47	-0.12***
	(0.49)	(0.50)	(0.02)
Washing machine	0.14	0.09	-0.05***
	(0.35)	(0.29)	(0.02)
Fridge	0.55	0.47	-0.08***
	(0.50)	(0.50)	(0.02)
Computer	0.10	0.07	-0.03***
	(0.30)	(0.26)	(0.01)
Television	0.94	0.93	-0.01**
	(0.24)	(0.26)	(0.01)
Fan	0.97	0.97	-0.00
	(0.16)	(0.17)	(0.01)
Electricity	0.99	0.94	-0.06***
	(0.08)	(0.24)	(0.01)
Car	0.05	0.05	0.00
	(0.21)	(0.21)	(0.01)
Tractor	0.02	0.02	0.00
	(0.14)	(0.15)	(0.00)
Bike	0.77	0.74	-0.03**
	(0.42)	(0.44)	(0.01)
Bicycle	0.46	0.35	-0.11***
	(0.50)	(0.48)	(0.02)
N. of Obs.	3,419	18,457	

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Comparing TN ECE Baseline sample to NFHS - Household characteristics

	(1) NFHS-V sample	(2) Baseline sample	(3) Difference
Panel B: Other characteristics			
Number of children (2-7 yrs old)	1.36	1.36	-0.00
	(0.56)	(0.54)	(0.01)
Scheduled caste	0.36	0.33	-0.04*
	(0.48)	(0.47)	(0.02)
Owns land	0.30	0.23	-0.07***
	(0.46)	(0.42)	(0.02)
N. of Obs.	3,419	18,457	
Panel C: Parental education			
Mother education: at least some primary	0.96	0.96	-0.00
	(0.20)	(0.20)	(0.00)
Mother education: at least some secondary	0.87	0.93	0.06***
	(0.33)	(0.25)	(0.01)
N. of Obs.	3,399	16,932	

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Comparing attriters to non-attriters

	(1) Surveyed a at follow-up	(2) Attrited	(3) Difference (overall)	(4) Difference (village FE)
Male	0.51	0.50	-0.00	-0.00
	(0.50)	(0.50)	(0.01)	(0.01)
	[5,267]	[19,152]	[24,419]	[24,419]
Mother Edu: $<$ Gr. 9	0.32	0.35	0.03**	0.00
	(0.47)	(0.48)	(0.01)	(0.01)
	[5,267]	[19,152]	[24,419]	[24,419]
Mother Edu: Gr. 9-11	0.31	0.32	0.01	0.02**
	(0.46)	(0.47)	(0.01)	(0.01)
	[5,267]	[19,152]	[24,419]	[24,419]
Mother Edu: Gr. 12+	0.37	0.33	-0.04**	-0.03**
	(0.48)	(0.47)	(0.02)	(0.01)
	[5,267]	[19,152]	[24,419]	[24,419]
SES Decile	5.07	4.96	-0.11	0.10
	(3.00)	(2.84)	(0.10)	(0.07)
	[5,267]	[19,152]	[24,419]	[24,419]
Math (2019)	-0.01	0.00	0.01	0.06***
	(1.16)	(1.09)	(0.02)	(0.02)
	[5,267]	[19,152]	[24,419]	[24,419]
Tamil (2019)	-0.01	0.00	0.01	0.03**
	(0.67)	(0.64)	(0.01)	(0.01)
	[5,267]	[19,152]	[24,419]	[24,419]
Age at baseline (months)	56.99	55.82	-1.17***	-1.52***
	(20.08)	(19.46)	(0.35)	(0.35)
	[5,267]	[19,152]	[24,419]	[24,419]

Back

Difference in resources, inputs and child activities by maternal education

	(1) Primary or less	(2) Incomplete secondary	(3) Grade 12 or more	(4) (3)-(1)	(5) Math value added	(6) Tamil value added
Video classes	0.08	0.12	0.22	0.136***	.2***	.081***
	(0.27)	(0.32)	(0.41)	(0.41)	(.048)	(.024)
Audio classes	0.04	0.08	0.12	0.069***	.052	.0032
	(0.20)	(0.27)	(0.32)	(0.32)	(.057)	(.031)
In-person classes	0.08	0.08	0.04	-0.039***	.028	.0052
	(0.28)	(0.27)	(0.21)	(0.21)	(.045)	(.034)
School sent homework	0.13	0.19	0.27	0.125***	.15***	.045**
	(0.33)	(0.40)	(0.44)	(0.44)	(.046)	(.019)
HH member teaches child	0.62	0.77	0.83	0.192***	.095**	.08***
	(0.48)	(0.42)	(0.37)	(0.37)	(.038)	(.019)
Private tutoring	0.17	0.16	0.12	-0.065***	.15***	.048**
	(0.38)	(0.37)	(0.33)	(0.33)	(.038)	(.02)
Child can access TV	0.78	0.81	0.80	0.002	.097**	.062***
	(0.41)	(0.39)	(0.40)	(0.40)	(.045)	(.022)
Child can access smartphone	0.50	0.62	0.76	0.248***	.011	-.0051
	(0.50)	(0.48)	(0.43)	(0.43)	(.038)	(.021)
Child can access phone internet	0.21	0.28	0.37	0.135***	-.025	-.0086
	(0.41)	(0.45)	(0.48)	(0.48)	(.042)	(.02)
Child can access computer	0.01	0.02	0.06	0.052***	.13	.039
	(0.12)	(0.13)	(0.24)	(0.24)	(.083)	(.043)
Child can access WiFi	0.00	0.01	0.03	0.029***	.094	.0027
	(0.04)	(0.07)	(0.17)	(0.17)	(.13)	(.059)
Used YouTube for edu content	0.28	0.45	0.56	0.246***	.088**	.056**
	(0.45)	(0.50)	(0.50)	(0.50)	(.036)	(.022)
Used Educational TV	0.52	0.55	0.50	-0.047**	.11***	.064***
	(0.50)	(0.50)	(0.50)	(0.50)	(.029)	(.017)
Used books from school	0.75	0.76	0.77	0.019	.12***	.055**
	(0.43)	(0.43)	(0.42)	(0.42)	(.045)	(.022)
Used books from home	0.40	0.46	0.52	0.086***	.045	.048***
	(0.49)	(0.50)	(0.50)	(0.50)	(.033)	(.017)
Used other internet resources	0.03	0.04	0.07	0.047***	-.065	-.0024
	(0.17)	(0.21)	(0.26)	(0.26)	(.054)	(.033)
No. of Obs.	1,782	1,633	1,696	3,478	5,111	5,111

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Difference in resources, inputs and child activities, by *(ITK)* attendance

	(1) Does not attend ITK	(2) Attend ITK	(3) Difference (overall)	(4) Difference (village FE)
Video classes	0.23	0.06	-0.17***	-0.15***
	(0.42)	(0.24)	(0.01)	(0.01)
	[3,830]	[5,136]	[8,966]	[8,966]
Audio classes	0.09	0.06	-0.03***	-0.02***
	(0.29)	(0.24)	(0.01)	(0.01)
	[3,830]	[5,136]	[8,966]	[8,966]
In-person classes	0.04	0.09	0.06***	0.06***
	(0.19)	(0.29)	(0.01)	(0.01)
	[3,830]	[5,136]	[8,966]	[8,966]
School sent homework	0.37	0.27	-0.10***	-0.07***
	(0.48)	(0.44)	(0.02)	(0.01)
	[3,830]	[5,136]	[8,966]	[8,966]
HH member teaches child	0.86	0.87	0.01	0.01
	(0.34)	(0.33)	(0.01)	(0.01)
	[3,830]	[5,136]	[8,966]	[8,966]
Private tutoring	0.14	0.10	-0.04***	-0.01
	(0.35)	(0.30)	(0.01)	(0.01)
	[3,830]	[5,136]	[8,966]	[8,966]
Child can access TV	0.92	0.94	0.01	0.02***
	(0.26)	(0.24)	(0.01)	(0.01)
	[3,829]	[5,136]	[8,965]	[8,965]
Child can access smartphone	0.78	0.71	-0.07***	-0.06***
	(0.42)	(0.45)	(0.01)	(0.01)
	[3,829]	[5,136]	[8,965]	[8,965]
Child can access phone internet	0.52	0.48	-0.04**	-0.04***
	(0.50)	(0.50)	(0.02)	(0.01)
	[3,829]	[5,136]	[8,965]	[8,965]
Child can access computer	0.03	0.02	-0.01**	-0.01
	(0.17)	(0.14)	(0.00)	(0.00)
	[3,829]	[5,136]	[8,965]	[8,965]
Child can access WiFi	0.02	0.01	-0.01	-0.00
	(0.14)	(0.12)	(0.00)	(0.00)
	[3,829]	[5,136]	[8,965]	[8,965]
Used YouTube for edu content	0.56	0.47	-0.09***	-0.07***
	(0.50)	(0.50)	(0.02)	(0.01)
	[3,829]	[5,136]	[8,965]	[8,965]
Used Educational TV	0.44	0.65	0.21***	0.22***
	(0.50)	(0.48)	(0.01)	(0.01)
	[3,829]	[5,136]	[8,965]	[8,965]
Used books from school	0.86	0.95	0.09***	0.11***
	(0.35)	(0.22)	(0.01)	(0.01)
	[3,829]	[5,136]	[8,965]	[8,965]
Used books from home	0.61	0.57	-0.04*	-0.04**
	(0.49)	(0.49)	(0.02)	(0.01)
	[3,829]	[5,136]	[8,965]	[8,965]
Used other internet resources	0.07	0.05	-0.02**	-0.01
	(0.25)	(0.22)	(0.01)	(0.01)
	[3,829]	[5,136]	[8,965]	[8,965]

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Sensitivity of *Illam Thedi Kalvi* estimates to including further inputs

	Math				Tamil			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
If child attends ITK	.17***	.16***	.17***	.16***	.093***	.09***	.092***	.083***
	(.026)	(.026)	(.025)	(.025)	(.015)	(.015)	(.015)	(.014)
Age at endline (months)	.018***	.018***	.018***	.017***	.015***	.015***	.014***	.014***
	(.0012)	(.0012)	(.0012)	(.0012)	(.00069)	(.00069)	(.00068)	(.00068)
Male	-.12***	-.12***	-.12***	-.11***	-.094***	-.096***	-.095***	-.089***
	(.019)	(.019)	(.019)	(.019)	(.011)	(.011)	(.011)	(.011)
Mother Edu: Gr. 9-11	.14***	.13***	.12***	.11***	.066***	.058***	.053***	.05***
	(.029)	(.029)	(.029)	(.029)	(.016)	(.016)	(.016)	(.016)
Mother Edu: Gr. 12+	.18***	.16***	.14***	.13***	.1***	.087***	.081***	.078***
	(.03)	(.03)	(.03)	(.03)	(.017)	(.017)	(.017)	(.017)
SES Decile	.016***	.01**	.008*	.0073*	.0055**	.0029	.0018	.0015
	(.0042)	(.0042)	(.0042)	(.0041)	(.0021)	(.0021)	(.0021)	(.0021)
Government school (2021-22)	.59***	.6***	.58***	.49***	.31***	.31***	.3***	.24***
	(.055)	(.054)	(.053)	(.056)	(.028)	(.028)	(.028)	(.032)
Private school (2021-22)	.9***	.88***	.79***	.7***	.37***	.36***	.32***	.27***
	(.058)	(.058)	(.058)	(.061)	(.032)	(.032)	(.032)	(.036)
Resources for remote instruction:								
TV		.14***	.14***	.096**		.062**	.06**	.022
		(.042)	(.041)	(.043)		(.024)	(.024)	(.025)
Smartphone		.17***	.14***	.11***		.088***	.078***	.062***
		(.035)	(.035)	(.039)		(.02)	(.02)	(.021)
Phone internet		-.05	-.05	-.073*		-.025	-.026	-.04*
		(.039)	(.038)	(.037)		(.022)	(.022)	(.021)
Computer		.15**	.13**	.1		.11***	.1***	.082**
		(.067)	(.066)	(.066)		(.036)	(.036)	(.037)
WiFi		.11	.11	.044		.022	.019	-.029
		(.099)	(.099)	(.096)		(.056)	(.057)	(.055)
Compensatory inputs from parents and schools:								
Video classes			.21***	.2***			.084***	.082***
			(.041)	(.041)			(.023)	(.023)
Audio classes			-.046	-.064			.011	-.0042
			(.053)	(.053)			(.028)	(.027)
In-person classes			-.011	-.021			.022	.014
			(.044)	(.044)			(.022)	(.022)
School sent homework			.055*	.044			.016	.009
			(.029)	(.029)			(.017)	(.017)
HH member teaches child			.056	.037			.034*	.019
			(.036)	(.036)			(.018)	(.018)
Private tutoring			.073**	.064*			.055***	.048***
			(.037)	(.036)			(.018)	(.018)
Child educational activities:								
YouTube for edu content				.069**				.027*
				(.03)				(.015)
Educational TV				.071***				.072***
				(.025)				(.014)
Books from school				.15***				.097***
				(.047)				(.027)
Books from home				.028				.03**
				(.03)				(.015)
Other internet resources				.16***				.1***
				(.052)				(.03)
Constant	-1.9***	-2***	-2.1***	-2.1***	-1.1***	-1.2***	-1.2***	-1.2***
	(.12)	(.13)	(.13)	(.13)	(.07)	(.073)	(.074)	(.074)
N. of obs.	8,902	8,901	8,901	8,901	8,902	8,901	8,901	8,901
R-squared	.38	.39	.39	.39	.45	.45	.46	.46

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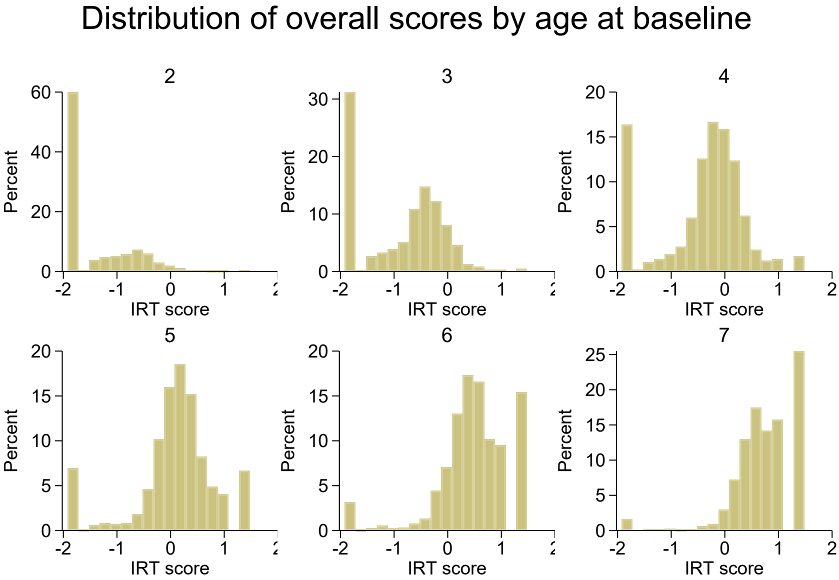
Raw distribution at baseline



Raw distribution at the follow-up