Access to Technology and Math Proficiency among Students: Empirical Evidence from India

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Outline

The Premise

- United Nations SDG 4: Need for quality education for children
- Access to digital technology resources such as computers, laptops constitute an important part of the education infrastructure necessary to achieve this goal. Why?
    - To access digital learning resources.
    - To continue learning in times of crises. For instance, COVID-19 Pandemic.
    - To learn in LMICs when traditional classroom learning is out of reach or inadequate (Hanushek, 2013; Adukia, 2017; Dhawan, 2020; Fuller, 1985)
- For Youth: Provides digital skills needed for digitalized labor markets

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- For Youth: Provides digital skills needed for digitalized labor markets

Current Status

- Considerable geographic heterogeneity in access to these digital resources
- SDG Indicator (4.a.1): Percentage of upper secondary schools with access to computers (2016)
  - High Income Countries: 97.62%
  - Low Middle Income Countries: 70.87%
  - Low Income Countries: 33.37%
- Access to computers at home (ITU, 2019):
  - Developed Countries: 82.3%
  - Developing Countries: 38.5%
- Measure to close the gap: Laptop dissemination programmes in LMICs

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Existing Evidence

- Empirical evidence on the educational impacts of laptops or home computers has remained mixed (Murnane and Ganimian, 2014)
  - Most studies find little to no impacts on test scores and cognitive skills of students (Beuermann et al., 2015; Cristia et al., 2017; Fairlie and Robinson, 2013; Hall, Lundin and Sibbmark, 2021)
  - Some studies find negative impacts on math and language skills as well as grades of students (Mora, Escardíbul and Di Pietro, 2018; Malamud and Pop-Eleches, 2011)
  - However, Mo et al. (2013) finds positive causal effect on math scores in China.
  - Studies have been conducted in both developed and developing country contexts such as, in the US, Sweden, China, Peru, Catalonia, and Romania.
- Studies do not point towards differential impacts of computers on educational outcomes of boys and girls (Fairlie, 2016)
- However, some evidence suggests that they can worsen socio-economic inequalities (Hall, Lundin and Sibbmark, 2021)

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This Paper

- We study the impact of a laptop distribution programme on math proficiency of students
- We also explore the effect of the program on other education related outcomes that can serve as potential channels for our effects.
- Tamil Nadu Free Laptop Scheme (*TFLS*), launched in 2011 in Tamil Nadu
  - First state programme of its kind in India, with many states following in its footsteps.
  - Estimated expenditure of over $600 million in first 3 years to distribute over 2 million laptops.
  - Much larger in scale compared to other programmes in the world. For instance, One Laptop Per Child (OLPC).

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Preview of Results

- Primary Outcome
  - Positive Impact on math proficiency
  - Effect size: 1.3% to 2.3%
- Potential Channels and Impact
  - Positive impact on english proficiency
  - Positive impact on hours spent in school and on hours spent doing homework
  - Negative impact on private tuition
- Heterogeneous Effects
  - Students from resources constrained households likely to be main beneficiaries of the programme
  - Suggestive evidence of narrowing the 'reverse gender gap' in math proficiency.

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Contribution

- Provides estimates for the impact of laptop access on *upper secondary students*
  - Most of the existing work on primary and middle school students (Beuermann et al., 2015; Cristia et al., 2017; Bulman and Fairlie, 2016)
  - Potential for immediate short term implications on post-secondary education or labor market decisions/ opportunities
- Points towards benefits of technology in closing learning gaps
  - Across Economic status and Gender
  - Boys and students from poorer economic background tend to catch up!
- Studies a large scale government program to provide access to laptops for students
  - In contrast to some of the existing studies relying on interventions conducted by NGO's
  - Can have potential implications for generalizability of results

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Tamil Nadu Free Laptop Scheme (TFLS)

- TFLS was launched in the state of Tamil Nadu on 15th September 2011.
- Tamil Nadu in brief (2011 Census):
  - A southern state in India Map
  - Sixth largest state by population (72 million) and Tenth largest by area in India
  - Sex ratio: 995 females per 1000 males (India avg. 943 females to 1000 males)
  - Literacy rate: 80.09% (India avg. 74.04%)
- The scheme was initially announced as a poll promise in run up to 2011 Tamil Nadu elections by AIADMK Party in which they formed the government
- The incumbent ruling party, DMK, also had a similar policy targeted only at college students in their manifesto for the elections.

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Tamil Nadu Free Laptop Scheme (TFLS)

- The scheme aimed to provide free laptops to students studying in government or government aided higher secondary schools and colleges.
- Rationale:
  - Invest in human resource potential of the state
  - Develop digital skills in youth to enable participation in the IT oriented labor market
  - Bridge digital divide between government school students and private school students having differential access to digital resources
- Phased Roll-out of the Programme:
  - Initial Phase (2011-2014): Students studying in Class 12th and in different years of undergraduate courses eligible for free laptops.
  - Programme implemented simultaneously in all districts of the state

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Identification Strategy

- Exploit plausible exogenous variation in the implementation of the *TFLS* program to understand effect on math proficiency of students
- We know that, government school students studying in *class 12th* at the *time of policy introduction* in *Tamil Nadu* were eligible for free laptops.
- We, therefore, use a triple difference (Difference-in-difference-in-differences or DDD) design to understand the causal effect of TFLS
- The three dimensions of our DDD framework are *cohort, time*, and *state*
  - Eligible cohort: Class 12, Ineligible cohort: Class 11
  - Pre-policy period: 2008-2010, Post-policy period: 2011-2012
  - Treated State: Tamil Nadu, Control: Other regions of India

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- We compare the learning outcomes of our *eligible cohort* (class 12th) to that of the *ineligible cohort* (class 11th) across our *treated* state of Tamil Nadu and other *control* states in India, *before* and *after* the program.
- Key Points:
  - We restrict our analysis to school going children as learning outcomes are less likely to be comparable across school and colleges
  - Furthermore, our main data source only provides information on school going children
  - Our data also limits us to study outcomes of children in the rural areas only
  - We restrict our analysis till year 2012 in order to have a clean identification design as other states started implementing similar programmes from 2013

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Data

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- Annual Status of Education Report (ASER)
    - A nationally representative annual household survey conducted by NGO Pratham in India
    - Covers over 600,000 students annually
    - Extensively used in education literature (Chakraborty and Jayaraman, 2019; Shah and Steinberg, 2019; Adukia, 2017)
    - We use data from 2008-2012 for the purpose of our study
    - Survey provides information on math proficiency of school going children in rural areas
    - Acts as a 'floor test' as the questions test only the foundational skills in arithmetic
    - Measurement of Math Score includes the following categories: Can't do any math, Recognize Numbers (1-9), Recognize Numbers (11-99), Subtraction, Division; Mean Score for our sample = 3.776

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+ \beta_7 \cdot (Post) + \gamma_1 \cdot X_i + \gamma_2 \cdot X_h + \gamma_3 \cdot X_v + \epsilon_{ihvs} \quad (1)
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Control variables | Parallel Trends | DDD estimate from base year 2008

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Results

Table: Impact on Math Proficiency: DDD Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Eligible × *Treated* × *Post*	0.017	0.049**	0.082***	0.066***	0.081***	0.087***
	(0.021)	(0.024)	(0.018)	(0.019)	(0.020)	(0.019)
R^2	0.016	0.09	0.09	0.09	0.10	0.12
Observations	30,981	30,017	25,908	21,696	21,696	21,696
Individual Controls	No	Yes	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes	Yes
Village Controls	No	No	No	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	Yes	Yes
State Fixed Effects	No	No	No	No	No	Yes

Notes: Robust standard errors clustered at the state level are reported in parentheses. *** p<0.01 **p<0.05 *p<0.1

Potential Channels

Table: Potential Channel: Impact on English Proficiency

		Meaning	
	English Reading Score	English Words	English Sentences
	(1)	(2)	(3)
Eligible × *Treated* × *Post*	0.030	0.400**	0.030*
	(0.081)	(0.078)	(0.016)
R^2	0.10	0.09	0.04
Observations	8,998	770	7,169

Notes: Regressions include individual, household and village level controls as well as state and time fixed effects. Robust standard errors clustered at the state level are reported in parentheses. *** p<0.01 **p<0.05 *p<0.1

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Potential Channels

Table: Impact on Educational Outcomes: IHDS Data

	School Hrs/Week	Homework Hrs/Week	Absent Days/Month
	(1)	(2)	(3)
Eligible × *Treated* × *Post*	8.879***	1.976**	0.713
	(1.573)	(0.741)	(1.026)
R^2	0.12	0.15	0.15
Observations	2,515	2,522	2,504

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Potential Channels

Table: Impact on Private Tuition

	ASER	IHDS
	Paid Tuition	Pvt. Tuition Hrs/Week
	(1)	(2)
Eligible × Treated × Post	-0.079***	-2.866***
	(0.019)	(0.760)
R^2	0.18	0.17
Observations	17,856	2,437

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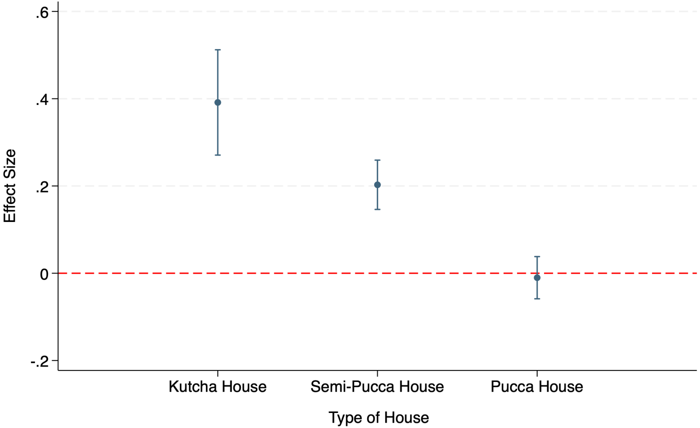
Sub-sample Analysis: Economic Status

Figure: Sub-sample Analysis for Housing Quality



Sub-sample Analysis: Gender

Table: Math Proficiency: Sub-sample Analysis for Gender

	Sub-sample: Boys=1	Sub-sample: Girls=1
	(1)	(2)
Eligible × *Treated* × *Post*	0.113***	0.061**
	(0.030)	(0.023)
R^2	0.11	0.13
Observations	10,935	10,761

Notes: Regressions include individual, household and village level controls as well as state and time fixed effects. Robust standard errors clustered at the state level are reported in parentheses. *** p<0.01 **p<0.05 *p<0.1

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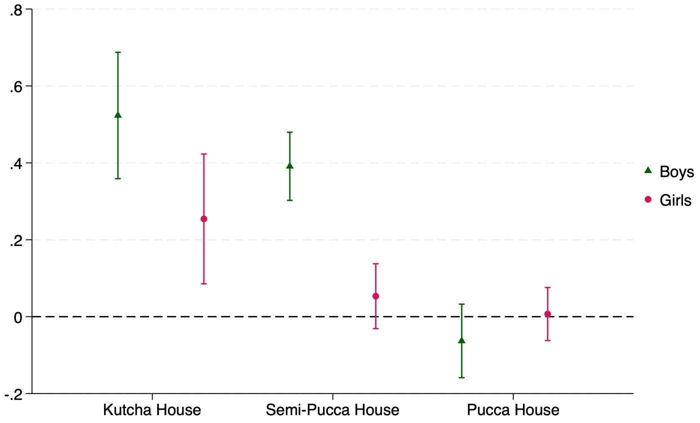
Sub-sample Analysis: Gender

Figure: Sub-sample Analysis for Gender based on Housing Quality



Robustness Checks

- Cohort falsification Link
- Quadruple Difference (DDDD) Link
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Conclusion

- The study provides causal evidence for positive impacts of access to laptops on math proficiency of students.
- Improved understanding and comprehension of English language, more time spent on learning, and reduction in potentially low quality private tutoring serve as plausible mechanisms for this effect
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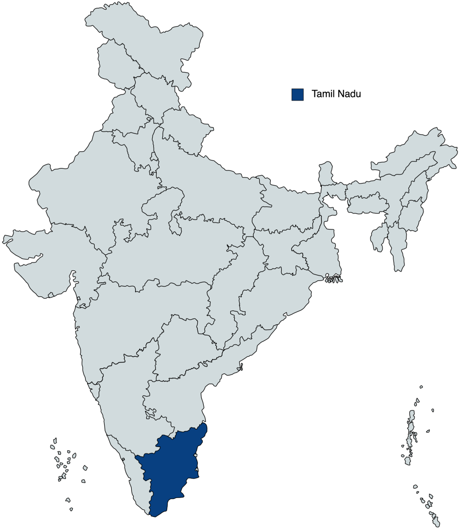
Thank you.

Happy to take questions and suggestions!

Tamil Nadu Free Laptop Scheme (TFLS)



Southern States Sub-sample

Table: Impact on Math Proficiency: Sub-sample of Southern States

	(1)
Eligible × *Treated* × *Post*	0.065*
	(0.027)
R^2	0.07
Observations	5,892
Controls	Yes
Year Fixed Effects	Yes
State Fixed Effects	Yes

Notes: Robust standard errors clustered at the state level are reported in parentheses. *** $p<0.01$ **$p<0.05$ *$p<0.1$

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Synthetic Controls

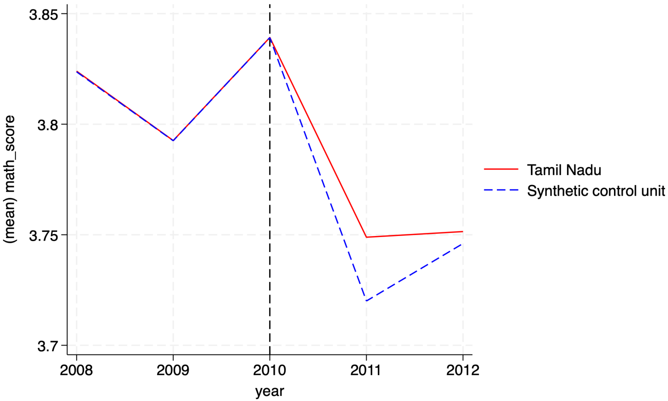

Figure: Synthetic Controls

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Unelectrified Households

Table: Impact on Math Proficiency : Unelectrified Households

	(1)
Eligible $\times$ *Treated* $\times$ *Post*	-0.0003
	(0.067)
R^2	0.25
Observations	2,531
Controls	Yes
Year Fixed Effects	Yes
State Fixed Effects	Yes

Notes: Robust standard errors clustered at the state level are reported in parentheses. *** p<0.01 **p<0.05 *p<0.1

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Cohort Falsification

Table: Impact on Math Proficiency: Cohort Falsification

	(1)
Eligible $\times$ *Treated* $\times$ *Post*	-0.051
	(0.031)
R^2	0.08
Observations	81,036
Controls	Yes
Year Fixed Effects	Yes
State Fixed Effects	Yes

Notes: Robust standard errors clustered at the state level are reported in parentheses. *** $p<0.01$ **$p<0.05$ *$p<0.1$

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Quadruple Difference

Table: Impact on Math Proficiency: DDDD Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Eligible × *Treated* × *Post* × *School_Type*	0.013	0.045*	0.061**	0.047**	0.051**	0.066***
	(0.029)	(0.025)	(0.022)	(0.022)	(0.022)	(0.021)
R^2	0.015	0.07	0.08	0.08	0.09	0.10
Observations	49,306	47,975	41,163	34,863	34,863	34,863
Individual Controls	No	Yes	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes	Yes
Village Controls	No	No	No	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	Yes	Yes
State Fixed Effects	No	No	No	No	No	Yes

Notes: Robust standard errors clustered at the state level are reported in parentheses. *** $p<0.01$ **$p<0.05$ *$p<0.1$

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Level of clustering

Table: Impact on Math Proficiency : Level of clustering

	(1)	(2)	(3)
TFLS	0.087*	0.087***	0.087***
	(0.046)	(0.010)	(0.006)
R^2	0.12	0.12	0.12
Observations	21,696	21,696	21,696
Controls	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes
Clustering Level	District	State × Year	State × Cohort

Notes: Robust standard errors clustered at different levels are reported in parentheses. *** $p<0.01$ **$p<0.05$ *$p<0.1$

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Parallel Trends

Table: Impact on Math Proficiency: Testing for Parallel Trends

	(1)	(2)	(3)	(4)	(5)	(6)
Eligible $\times$ *Treated* $\times$ *Year*	-0.012	-0.012	-0.005	0.008	0.008	0.012
	(0.014)	(0.015)	(0.010)	(0.013)	(0.012)	(0.012)
R^2	0.001	0.10	0.11	0.11	0.11	0.13
Observations	18,047	17,317	15,318	12,633	12,633	12,633
Individual Controls	No	Yes	Yes	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	Yes	Yes
Village Controls	No	No	No	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	Yes	Yes
State Fixed Effects	No	No	No	No	No	Yes

Notes: Robust standard errors clustered at the state level are reported in parentheses. *** p<0.01 **p<0.05 *p<0.1

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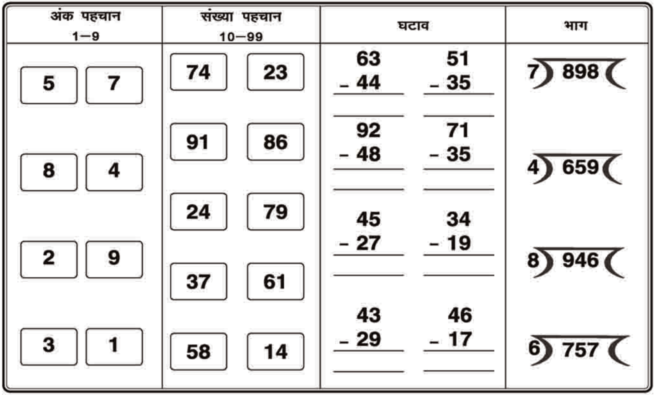
Sample Test Exercises in Math

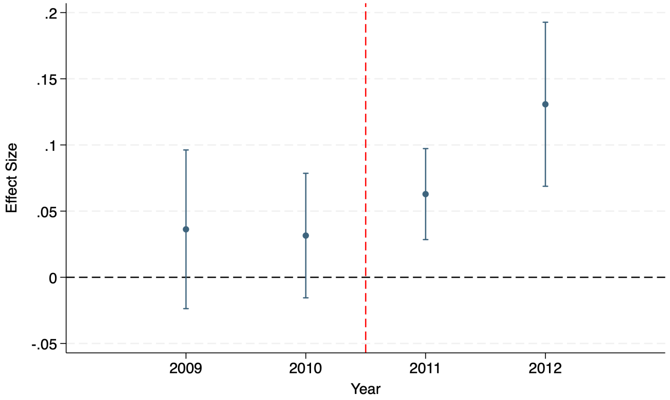
Figure: Sample Test Exercises in Math



अंक पहचान 1–9		संख्या पहचान 10–99		घटाव		भाग
5	7	74	23	63 − 44	51 − 35	7) 898 (
8	4	91	86	92 − 48	71 − 35	4) 659 (
2	9	24	79	45 − 27	34 − 19	8) 946 (
3	1	37	61	43 − 29	46 − 17	6) 757 (
		58	14			

Triple Difference Estimates from Base Year 2008

Figure: Triple Difference Estimates from Base Year 2008



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Control Variables

- Individual level: child age, child gender, mother's schooling status, mother's age
- Household level: number of household members, electricity connection in the household, electricity in the household on the day of interview, type of household
- Village level: electricity in the village, bank in the village, and availability of a primary, a middle, a secondary, and a private school in the village

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