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“Harbinger of a New Era”? Evaluating the Effect of India’s Right to Education Act on Learning Outcomes

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“Harbinger of a New Era”?
Evaluating the Effect of India’s Right to Education Act on Learning Outcomes

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Abstract

India enacted the Right of Children to Free and Compulsory Education Act (RTE) into law in 2010. RTE created a constitutional right to education and included regulations for pupil-teacher ratios, public school infrastructure, education spending, and private school enrollment. I contribute to the literature by estimating the causal effect of RTE on measures of literacy, numeracy and school quality using data from an annual, nationally representative survey of over 600,000 children. I utilize a difference-in-differences approach, controlling for differing pre-trends, student-level characteristics and GDP, as well as grade, state and year fixed effects. I find that while RTE had a positive effect on public school infrastructure and teacher absence rates, it had a negative impact on most measures of literacy and numeracy skills for public school students. I explore possible channels through which RTE could have had this adverse effect and provide suggestive evidence that the fall in learning outcomes was not the result of changes in enrollment, the rise of private schools or changes in school infrastructure. Further investigation into unmeasured variables such as the quality of teachers, curricula and pedagogy is crucial in order to ensure that India can successfully educate its over 400 million children.

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All errors are mine alone.

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1. Introduction

In 1960, more than a decade after India gained independence from Great Britain, only 32% of children below the age of fourteen were in school. Five decades and several different education policies later in 2008, 6.9% of children were still out of school (Das 2013) and 84.4% of rural children could not read even basic words (ASER 2008). It was in this context that in 2009, India passed The Right of Children to Free and Compulsory Education (henceforth referred to as "Right to Education Act" or RTE) to provide all children between the ages of 6 and 14 the constitutional right to education[1].

The Right to Education Act was enacted into law in 2010 and declared to be revolutionary. The minister for Human Resource Development described RTE as the "harbinger of a new era[2]." The media was similarly laudatory, with The Times of India proclaiming in a headline after the passage of the law that "from today, every child has a right to education[3]." This act was not just about getting kids in school; the Prime Minister asserted that RTE was "committed to ensuring that all children, irrespective of gender and social category, have access to […] the skills, knowledge, values and attitudes necessary to become responsible and active citizens of India[4]."

Seven years after the enactment of the law, this paper is the first to estimate the causal impact of RTE on literacy and numeracy rates of students in Indian public schools. It uses data from the Annual Status of Education Report, a national yearly survey of around 600,000 children that measures basic reading and mathematical

[1] As mentioned in the abstract, India had a population of over 400 million people below the age of 18 in 2012 according to UNICEF (https://www.unicef.org/infobycountry/india_statistics.html).
[2] "India Passes Free Education Bill" 2009. *BBC.* 5 August. https://tinyurl.com/rte-bbc
[3] "From Today, Every Child Has a Right to Education." *The Times of India.* https://tinyurl.com/rte-toi
[4] "PM's Address on Fundamental Right of Children to Elementary Education." 2010. *The Hindu.* https://tinyurl.com/hindu-rte

skills. Exploiting the fact that one state in India (Jammu and Kashmir) was exempt from RTE, I use a difference-in-differences framework to evaluate the effect of the law. I control for differing pre-trends, GDP, student-level characteristics and state and year fixed effects and find that despite its ambitious rhetoric, RTE had a *negative* effect on reading and math abilities.

This is concerning, but not surprising. In this paper I corroborate previous research tracking Indian public schools (such as Muralidharan et al. 2017) that found improvements in physical infrastructure. However, this improvement in infrastructure is not associated with an improvement in learning outcomes (Educational Initiatives 2010, Walker 2011, Muralidharan and Zieleniak 2014). To evaluate multiple possible explanations as to why RTE had this effect, I run ordinary least squares regressions of state-level averages of student learning against school infrastructure and enrollment. I find no evidence to suggest that the fall in learning is driven by increased enrollment of unskilled students, by a greater share of students going to private schools or changes in school infrastructure and teacher absence. I suggest that if the difference-in-differences findings are robust, they would have to be explained by factors that are not measured in my data, such as the quality of teachers, curricula and pedagogical methods.

These findings are relevant because India's ability to provide a good education to its children is crucial for its success in the coming decades. Research has shown that education is related to higher levels of income, wealth and health (Spring 2000). For instance, a "10 percentage point increase in girls' primary enrolment" is associated with a decrease in "infant mortality by 4.1 deaths per 1000" (Bellamy 1999). Muralidharan (2013) also points out that the economic literature has established the relationship between education levels and growth (Barro 1991;

Benhabib and Spiegel 1994; Mankiw, Romer, and Weil 1992) and that primary education in developing countries is associated with positive returns at the micro-level (Duflo 2001; Duraisamy 2002). Since India is overwhelmingly a young country with about 20% of the world's 10-year-olds, universal primary education is especially important to achieve economic growth (UNFPA 2016). If RTE is failing in providing India's children with even basic skills, this compels urgent policy research and action.

The paper is laid out as follows. In Section 2, I present the history of education in India, the features of the Right to Education Act and summarize existing research in this area. Section 3 describes in detail the data used in this paper, along with its limitations. Section 4 lays out the identification strategy, possible concerns and robustness checks. Section 5 presents the results, while Section 6 involves a detailed discussion of plausible explanations for my results. Since I cannot conclusively prove the channel through which RTE had the discovered effect, I suggest possibilities for future research. The 7th and final section concludes.

2. Background

2.1. History of education in India[5]

The Indian government has repeatedly tried to achieve universal primary education. The broad contours of education policy in India through the ages are presented in S. K. Das' authoritative "India's Rights Revolution" (2013). In 1950, the constitution of newly independent India included a non-enforceable "Directive Principle" declaring that the state "shall endeavour to provide, within a period of ten years from the commencement of this Constitution, free and compulsory education for all children until they complete the age of fourteen years." However, in 1960, only

[5] This section uses research from my final paper for the class "EMR 124: Childhood, Adolescence, Youth and International Human Rights."

32% of students in this age group were in school. To operationalize the Directive Principle, the Government of India introduced the first National Policy on Education in 1968. This was followed by Operation Blackboard in 1987-8 that sought to improve the infrastructure and resources available to Indian schools, and an ambitious scheme in 1995 that incentivized enrollment and attendance through the provision of midday meals in schools.

To better understand the motivations in setting education policy, it is useful to track the successive Five Year Plans of the Planning Commissions of different governments in India (Kumar 2004) that lay out the country's policy priorities for each five-year period. The policy of universal primary education was included in the 1970s as part of "the minimum needs program." But it was the Sixth Five Year Plan (1980-85) that focused on those disadvantaged groups such as girls and members of scheduled castes in India who systematically lacked access to education. Further Five Year Plans looked to infrastructure improvements and curriculum restructuring, to make education accessible and relevant.

Despite these efforts, significant gaps in government provision of education remained. As of 1991, there were 371 million illiterate people in India (Kumar 2004). While this could be because people did not wish to go to school, governments in India were also failing to provide accessible schools to students. This is evidenced by the many policies that attempted to improve accessibility, for instance with the Eighth Five Year Plan (1992-97) proposing that a "center of learning […] be provided for every child within a walking distance of one kilometer from his or her home" (Kumar 2004).

Sarva Shiksha Abhiyan, a comprehensive policy aimed at universal primary education, is considered the predecessor of the Right to Education Act. Enacted in

2000, it introduced a target of ensuring that all children are in school by 2003. Once again, however, this target was missed. By 2008, 7% of children in the age group of 6-13 were still out of school. Of these students, a little over 34% were Muslim or belonged to a Scheduled Caste, Scheduled Tribe or Other Backward Class (groups designated as historically disadvantaged under Indian law). The 7% children not in school broke down into 2% being dropouts and 5% being never-enrolled (Das 2013). It was in this context that the Government of India introduced the Right to Education Act in 2009.

2.2. The Right to Education Act

The Indian parliament passed the Right to Education Act in 2009 amid much fanfare. The act required that all children of the ages 6-14 be educated. The appropriate state government, along with the local authority, was tasked with establishing a school in any neighborhood lacking a public school within three years after the enactment of the act. This was to be jointly funded by the central and state governments, with central funds provided in the form of grants. The act also prescribed a number of standards for public schools, including specific student-teacher ratios for different grades and infrastructure requirements. Children were required to be admitted to classes "appropriate to [their] age," and "in order to be at par with others […] receive special training." Private schools were required to set aside at least 25% of seats in their classes for students from the neighborhood belonging to "weaker sections" as defined by family income.

The act came into force in April 2010, but the Indian state of Jammu and Kashmir was exempt from following the act. This is in line with the special rights afforded to the state under Article 370 of the constitution since 1950. Under this Article, "Parliament's legislative power over the State [of Jammu and Kashmir is] restricted to three subjects—defence, foreign affairs and communications" (Noorani 4). Thus Jammu and Kashmir was the only area of the country that was exempted from RTE by statute.

There is very little research directly on the effect of the Right to Education Act. Evaluations of the Act have largely been done by governmental institutions or private sector organizations and are based simply on trends over time. For instance, the RTE evaluation by the firm KPMG indicates that enrollment, particularly of girls, has increased since the introduction of the act (KPMG). A report by the Ministry of Human Resource Development in India suggests that infrastructure in schools has improved slightly (MHRD), though not in rural areas (KPMG). The Annual Status of Education Report (ASER) published by Pratham, an Indian educational non-profit organization, has shown a fall in math and language abilities of students in India over the last decade. This fall could have happened despite the introduction of the act, or may have been caused by some aspect of the act such as increased enrollment or its stringent requirements.

2.3. The education literature

Despite the paucity of research specifically on RTE, a large body of literature in economics tries to understand the state of Indian education more generally, and is summarized well in Muralidharan (2013) and Mukerji and Walton (2012). This research includes large-scale representative surveys, natural experiments and randomized control trials. The literature attempts to understand the changes in the quality of education outcomes and infrastructure, as well as the impact of different policy interventions on learning outcomes.

Muralidharan et al. (2017) conduct a panel survey of over a thousand village schools in India and find "significant improvements in input-based measures of schooling quality" (Muralidharan 2013), with pupil-teacher ratios having fallen by 20%, increased school enrollment and improved infrastructure (such as toilets and electricity). However, learning outcomes have stagnated or worsened. Educational Initiatives' 2010 School Learning Study showed that the mean results of Indian public schools is "less than half that of the international mean" (Muralidharan 2013); this is corroborated by the Programme for International Student Assessment (Walker 2011) study that ranked the Indian states of Himachal Pradesh and Tamil Nadu worse than almost all other places measured (Muralidharan 2013). Even more concerning is that Muralidharan and Zieleniak (2014) find that most students measured at the end of a school year do not improve from their performance at the beginning.

That schools are improving while students are stagnating is a puzzle. A large amount of research from India and other developing countries reveals that "pupil-teacher ratios, infrastructure or measures of teachers' qualifications are typically unrelated to learning outcomes" (Mukherji and Walton 2012). Randomized control trials have shown that since students are largely placed in the class appropriate for their age and not their educational background, a policy of "teaching at the right level" by reorganizing classes on the basis of a test at the start of the year sees large returns (Banerjee et al. 2016). Other RCTs aimed at reducing the pupil-teacher ratio saw little effect (Banerjee et al. 2007), while targeted remedial camps do result in improvement (Banerjee et al. 2016).

This paper fills an important gap in the literature by rigorously evaluating the impact of RTE for the first time. It finds no evidence of an improvement in learning outcomes as a result of the act's enactment; in fact, the results show that RTE may have had a negative impact on students' learning. This paper confirms findings from the existing literature that school infrastructure and teacher absence rates have improved, and contributes evidence that RTE had a causal effect on these quality measures. Finally, I use state-level measures of school quality, enrollment and learning outcomes to evaluate possible channels for RTE's impact on learning outcomes and suggest avenues for future research in this domain.

3. Data

This paper uses data from the 2007-2014 Annual Status of Education Reports (ASER) published by a not-for-profit organization called Pratham. Pratham is one of India's largest non-governmental organizations and focuses on improving education quality in India. ASER is an annual survey conducted since 2005 across India that seeks to measure and track learning outcomes. Importantly, it is an entirely citizen-run survey and as such is independent of government influence. This ensures the impartiality of the data.

ASER data is representative at the district level. In each district, about 30 villages are sampled with probability proportional to size. 20 households per village are then randomly selected (Wadhwa 2014). Pratham's team of surveyors test all children aged 5-16 in the sampled households for their language and math skills. This results in a sample of between 320,000 and 350,000 households with an average of about 600,000 children every year. (ASER FAQ).

The most important parts of the ASER data are the learning outcome measurements. Children are tested on their ability to read letters, words, first grade level texts (a paragraph) and third grade level texts (story) in English and the local language. ASER also measures their ability to recognize one digit numbers, two digit numbers and do subtraction and division. Later versions of the survey also introduced questions on other skills such as telling time or using money. Figure 3 in the appendix presents sample language and math tests used in the survey.

The student-level characteristics collected have changed over time. Surveys include data on the kind of school the students go to if they are enrolled (private, public, madrassa or other), as well as students' grade and age. Some versions of the survey include parents' education. Some also measure the availability and quality of household infrastructure. However, since this is primarily a test of educational outcomes, the data collected on household and student characteristics is sparse and does not include religion, caste or income across years.

Additionally, ASER surveyed the public school with the largest enrollment in every village in 2007 and then yearly from 2009-14. Once again, while the range of questions has expanded and changed over time, many have remained constant. The survey measures the number of students enrolled in each grade, the number of students who were present on date of survey in each grade, the number of teachers (both full-time and contract), the number of teachers who were present, school infrastructure (such as blackboards, taps, toilets, etc.) and whether they are usable, and learning material (textbooks, notebooks). Some years also have data on whether the school recently received a government grant.

ASER is a rich and very large dataset. As a comparison, the 68th round of the NSS Consumer Expenditure Survey of the Government of India "sampled a total of 100,957 households, of which 59,129 were rural households" (ASER FAQ) which makes ASER about three times larger than an ambitious government-run survey. ASER's estimates of learning outcomes have been corroborated by other studies such as the India Human Development Survey, Education Initiative surveys, Program for International Student Assesment (PISA) tests and the Andhra Pradesh Randomized

Evaluation Studies (Pritchett 2014). As such, it is widely reputed to be a reliable and rigorous source of data on the quality of education in India.

It is especially reliable because it tests students at home. Surveyors find out the number of children that live in that household and test all of them; if children are away from home for some reason, the survey manual instructs surveyors to come back later and test them (ASER 2014). In comparison, the National Achievement Survey of the Government of India is conducted in schools[6]. However, if only motivated and smart students show up to school, the test would overestimate the skill level of the average student in an Indian school. Since ASER conducts the test at home on a weekend, it captures the learning measures of children regardless of whether they attend school regularly.

The ASER data has some drawbacks that limit the findings of this paper. The data is temporally limited. I only have ASER data for 8 years. Especially since the Right to Education came into effect in 2010, I only have 3 pre-implementation years. I exclude data from the year 2010 for two reasons. Since the law was enacted in this year, it is a transition year where the policy would have an unclear and heterogeneous effect. The survey was also not administered in Jammu and Kashmir in 2010 and including data from 2010 would not contribute to the analysis since Jammu and Kashmir is my control group. School-level data is also unavailable for all states for 2008.

Since sampling and measuring learning outcomes for 600,000 kids every year is a very difficult exercise, Pratham collects only very basic data on children. This makes it impossible to control for household characteristics such as income, religion, or caste that could have an impact on children's skills. Instead, I use state-level yearly

[6]Rosenberg, Tina. 2014. "In India, Revealing the Children Left Behind." The New York Times. 23 October. https://tinyurl.com/tnyt-rte

GDP data from the Planning Commission of India as a rough proxy for household income. I also use state and year fixed effects in my regressions to limit the effect of

Table 1: Summary statistics of students in dataset in 2007 and 2014

Variable	(1) 2007	(2) 2014
Age	9.380	9.533
	(3.629)	(3.856)
Male	0.534	0.460
	(0.499)	(0.498)
Public school	0.622	0.462
	(0.485)	(0.499)
Private school	0.177	0.233
	(0.382)	(0.423)
Read nothing	0.0715	0.0970
	(0.258)	(0.296)
Read at least letters	0.758	0.538
	(0.428)	(0.499)
Read at least words	0.634	0.433
	(0.482)	(0.495)
Read at least paragraph	0.503	0.354
	(0.500)	(0.478)
Read story	0.373	0.273
	(0.484)	(0.445)
Do no math	0.0718	0.0797
	(0.258)	(0.271)
Recognize at least 1-digit numbers	0.755	0.555
	(0.430)	(0.497)
Recognize at least 2-digit numbers	0.630	0.440
	(0.483)	(0.496)
Do at least subtraction	0.468	0.269
	(0.499)	(0.443)
Do division	0.290	0.152
	(0.454)	(0.359)
N	728644	639026

Data from ASER. Mean coefficients reported with standard deviations in parentheses.

unmeasured variables that do not change over time within a state (such as geography) or affect all of India simultaneously (such as a change in the party controlling the central government).

Furthermore, it is not possible to track kids across time or link data on children to data on schools. This limits the questions one can ask with the data—for instance, it is not possible to run a regression quantifying the relationship between improvements in school infrastructure and learning outcomes in that school. Instead, I analyze the two datasets separately to estimate the causal impact of RTE on each. I also run regressions using state-level averages of learning outcomes and school quality measures to suggest possible channels through which RTE had the discovered effect, though these state-level estimates are less precise than student- or school-level regressions would have been.

Table 1 presents the summary statistics for some main variables of interest in 2007 and 2014, which are the first and last years of data I use. The sample size has changed a little over time, from about 728000 children to 639026 children. There has been a decrease in the percentage of students in public schools from 62% to 46% and an increase in students in private schools from 17% to 23%. The percentages of students who can read nothing and do no math have risen, and the percentages of students who have the other skills measured by ASER have fallen.

4. Methodology

In this section, I outline the identification strategy used to estimate the causal effect of the enactment of the Right to Education Act in 2010 on various learning outcomes and school quality measures. I then describe possible theoretical issues with this approach, and the robustness checks used to verify my results. I finally describe the strategy used to explore the possible channels through which RTE could have caused the results that I find.

4.1. Traditional difference-in-differences approach

The first set of regressions employs a traditional difference-in-differences (DID) approach, comparing outcomes in the control state of Jammu and Kashmir (where the act was not implemented) to those in the rest of India[7] (where it was) before and after the enactment of the act in 2010. The outcomes of interest, measured for children in grades 1-8, are summarized below:

Table 2: Outcome variables of interest for DID regressions

Student-Level Language Skills Measures	
Read nothing	Equal to 1 if the student can read nothing at all
At least letters	Equal to 1 if the student can read at least letters
At least words	Equal to 1 if the student can read at least words
At least a paragraph	Equal to 1 if the student can read at least a paragraph (Grade 1 difficulty)
Read a story	Equal to 1 if the student can read a short story (Grade 2 difficulty)
Student-Level Math Skills Measures	
No math	Equal to 1 if the student can do no math
At least 1-digit nrs	Equal to 1 if the student can recognize at least one-digit numbers
At least 2-digit nrs	Equal to 1 if the student can recognize at least two-digit numbers (Grade 2 difficulty)
At least subtraction	Equal to 1 if the student can do at least subtraction
Division	Equal to 1 if the student can do division. (Grade 3-4 difficulty)
School-Level Quality Measures	
Grade 2 blackboard	Equal to 1 if the 2nd grade classroom in the school has a usable blackboard
Grade 4 blackboard	Equal to 1 if the 4th grade classroom has a usable blackboard
Percentage of teachers	Percentage of teachers employed at the school who are present on the day of the survey

Source: Variables constructed from ASER data.

[7] I only use those states for which I have education and GDP data. This includes all of the 28 states that existed in this period and 1 of the 7 union territories. A full list is available in Table 8 in the appendix.

The choice of variables merits some justification and clarification. If a student possesses “at least” a particular skill, the ASER data indicates the student as possessing either that skill or a higher skill from the table. “Language skills” refer to the language spoken locally. I use these measures, rather than measures of English ability, on the assumption that students and teachers in rural and public schools are more likely to be competent in the local language than in English[8]. These measures, therefore, should be taken as an upper bound on language ability. The hardest skills measured are the ability to read a short story (at the grade 2 level difficulty according to the official curriculum) and division (which is officially taught in grade 3 or 4). The difference in languages between states is not an issue for comparison, because these are very basic skills[9] that children ought have according to the state-mandated curriculum (ASER FAQ).

The school-level variables attempt to measure education “inputs”. The RTE places great emphasis on improving physical infrastructure, and hence dummy variables for the presence of usable blackboards in grades 2 and 4 are used as a proxy. The variable measuring the percentage of teachers present was constructed by dividing the number of teachers found to be present at the school on the day of the survey by the number of teachers officially employed at that school. Since teacher absence is a recorded problem in India and RTE attempts to improve pupil-teacher ratios, this is a useful variable to consider.

The formal difference-in-differences econometric model used is as follows:

Equation 1: Traditional difference-in-differences model

$$y_{ijt} = \beta_0 + \beta_1 \cdot treatmentgroup \cdot postRTE + \beta_{X_i} \cdot \boldsymbol{X_i} + \boldsymbol{\gamma}_t + \boldsymbol{\lambda}_j + \varepsilon_{ijt}$$

[8] ASER 2014 reports, for instance, that “just under half” of Grade 5 students can read a few sentences in their local language while only “about 25% […] could read simple English sentences.”
[9] Note that basic literacy and numeracy skills are pre-requisites for accessing any form of higher education—if you cannot read letters, you cannot read Aquinas.

where subscript i refers to the unit of measurement (student or school), subscript j to the state and subscript t to the year. y is the outcome variable. $\boldsymbol{X_i}$ is a set of controls. β_0 is the constant, $\boldsymbol{\gamma_t}$ are year fixed effects, $\boldsymbol{\lambda}_j$ are state fixed effects and ε_{ijt} the error terms. To overcome the issue of serially correlated standard errors (see Bertrand, Duflo and Mullainathan (2004) for a detailed discussion), all standard errors are clustered at the state-level.

β_1 is the coefficient of interest. It is the coefficient on an indicator variable equal to 1 when the state is not Jammu and Kashmir *and* the year is post-2010. Thus, when controlling for state and year fixed effects, β_1 should give us the effect of RTE on the outcome of interest. I call β_1 the "*traditional DID coefficient*" in tables and discussion. When interaction terms are included, the estimated effect of RTE is the sum of β and the coefficient of the interaction terms.

For the learning outcomes DID regressions, I use the following controls $\boldsymbol{X_i}$: an indicator equal to one if the student is male, an indicator for if the student goes to a private school, dummy variables for each of grades 1 through 7 (grade 8 omitted) and interaction terms that multiply the grade dummy variables with the treatment group indicator and the post-2010 time indicator. I also control for the log of GDP of the state in the year that the student was surveyed.

I include the grade-and grade-interaction dummies because RTE could have had different effects on students of different grades. I include the male indicator because a long tradition of son-preference in India (for instance, consider the "first boys" of Sen 2015) could result in differential impacts by gender. I control for going to a private school, because I am primarily interested in the performance of public schools under RTE. Finally, changes in income post-2010 could be causing my results and hence I control for state-level GDP.

4.2. Robustness check 1: Parallel pre-trends

The traditional DID approach depends on the treatment and control groups following parallel trends before the policy change. If the pre-trends were not similar, any effect seen could be due to differing trajectories, and not due to the introduction of the policy. In this section, I describe the tests conducted to check whether the treatment and control groups had parallel pre-trends, and a DID regression run controlling for different pre-trends.

I check for parallel pre-trends in two ways. First, I simply plot the averages of different outcome measures in the treatment and control groups across time. If the pre-trends are parallel and RTE has an effect, these lines should be parallel before 2010 and diverge after the introduction of the act. However, this is an imprecise way of checking for parallel pre-trends and hence I follow the method used in Acemoglu and Angrist (2001). I create dummy variables for each of the years in my sample. I interact each year dummy with an indicator equal to 1 if the observation is in the treatment group and 0 otherwise. I then regress the outcome variables against all of the interaction terms and plot the coefficients. If the pre-trends are parallel, these coefficients should be insignificant and close to zero for all years before 2010.

To ensure the robustness of my results, I then run a version of the DID regression that controls for non-parallel pre-trends. This approach is based on Mulaney (2016), who in turn draws on Bruich (2014) and Acemoglu and Angrist (2001). I create a "treatment x time trend" variable, which interacts being in the treatment group with a variable tracking the year of the observation. I also create a "treatment x post-RTE trend" variable, which interacts being in the treatment group with a variable tracking every year starting with 2010 in the sample (that is, it is equal to 0 for the years before 2010, equal to 1 in 2010, equal to 2 in 2011 and so on).

Equation 2: Trends-controlled difference-in-differences model:

$$y_{ijt} = \beta_0 + \beta_1 * treatment * postRTE + \beta_2 * treatment * timetrend$$
$$+\beta_{X_i} \cdot \boldsymbol{X_i} + \boldsymbol{\gamma}_t + \boldsymbol{\lambda}_j + \varepsilon_{ijt}$$

The above model uses the same subscripts as before. Once again, y is the outcome variable, α is the constant, $\boldsymbol{X_i}$ is the set of controls, $\boldsymbol{\gamma_t}$ are year fixed effects, $\boldsymbol{\lambda}_j$ are state fixed effects and ε_{ijt} the error terms. Standard errors are clustered at the state level. In this regression, the $treatment * timetrend$ term controls for differing linear trends in the treatment and control groups that existed *before* the introduction of the Right to Education Act. The coefficient on the $treatment * postRTE$ term, β_1, then accounts for differences in the outcome variable post-RTE over and above pre-existing differences. β_1 is thus the coefficient of interest that estimates the effect of RTE controlling for differing pre-trends and I call it the "*trends-controlled DID coefficient*" or the "*trends-controlled DID estimate*".

4.2. Robustness check 2: Omitted variables

The DID approach also assumes that the introduction of RTE was the only factor that affected the treatment and control groups differentially. For instance, some other change in education policy in the control group, rather than introduction of RTE in the treatment group, could be causing the results. To the best of my knowledge, there were no other big changes in educational policy that could have had a differential effect on the control state of Jammu and Kashmir and the rest of India in this period. I also control for student-level factors that are available in the ASER report and include state and year fixed effects. Unfortunately, DID still cannot conclusively prove that RTE drives the regression results. To have full confidence in these results, they need to be corroborated by more evidence.

However, I do conduct one robustness check to limit the effect of omitted variables. I rerun the trends difference-in-differences regression described above on all the outcome variables of interest, but with a smaller treatment group. Instead of comparing outcomes in the control state of Jammu and Kashmir with outcomes in the rest of India, I just compare them to outcomes in the neighboring states of Punjab and Himachal Pradesh. Since these states are geographically contiguous, I can rule out changes in the weather (such as a particularly strong monsoon season, which could have a negative effect on student attendance and school infrastructure) and changes in culture as driving the results. This also limits the effect of economic changes, since economic conditions and industries are unlikely to differ significantly on either side of a state border. On the other hand, the smaller sample size also reduces power and makes it harder to identify an impact.

4.3. Exploring possible channels

RTE is a complex law that comprises many different provisions. Even if the trends DID estimator gives us the causal effect of RTE on learning outcomes, it still does not tell us *why* RTE had the effect that it did. A conclusive answer to this question is beyond the scope of this paper, but I suggest some possible explanations in the "Discussion" section.

To motivate the discussion, I run an ordinary least squares (OLS) regression on 2010-2014 data from states that were affected by RTE and on which I have education and GDP data[10]. The unit of observation is thus at the state-year level. The dependent variables are percentages of students who possess the literacy and numeracy skills listed in Table 2 above. The independent variables from ASER are the percentage of students that are enrolled in school, the share of enrolled students

[10] See Table 8 in the appendix for a full list of states.

who go to private schools, the percentage of schools with a usable blackboard in grade 2 and the average percentage of teachers present at a school. In addition, I control for economic changes with logged GDP. Nevertheless, I cannot rule out omitted variable bias and hence these results should be considered with caution.

This basic OLS regression also suffers from serious reverse causality concerns. For instance, if an increase in teacher attendance is associated with a statistically significant positive effect on learning outcomes, it could be that more teachers coming to work caused outcomes to improve. However, it could also be that better learning levels encouraged teachers to work harder and show up to school to teach. To circumvent some of these reverse causality issues, I run a second version of the regression that includes lagged versions of the enrollment, infrastructure and teacher attendance variables.

5. Results

5.1. Effect of RTE on learning outcomes

Table 9 in the appendix shows the results of the traditional difference-in-differences regressions on language skills over time. Table 10 shows the results of the DID regressions on math skills over time. These regressions measure the effect of treatment (being outside Jammu and Kashmir post 2010) on different grade levels, controlling for logged GDP of the state that year, for whether the student is male, for studying at a private school, and for state, year and grade fixed effects. Due to the interaction terms, the effect of treatment for students in a particular grade is the sum of the coefficient on the interaction term for that grade and the general difference-in-differences coefficient. Standard errors are clustered at the state level. It is important to recognize that the traditional DID estimates should be approached with caution, since they are based on strong assumptions that I discuss below.

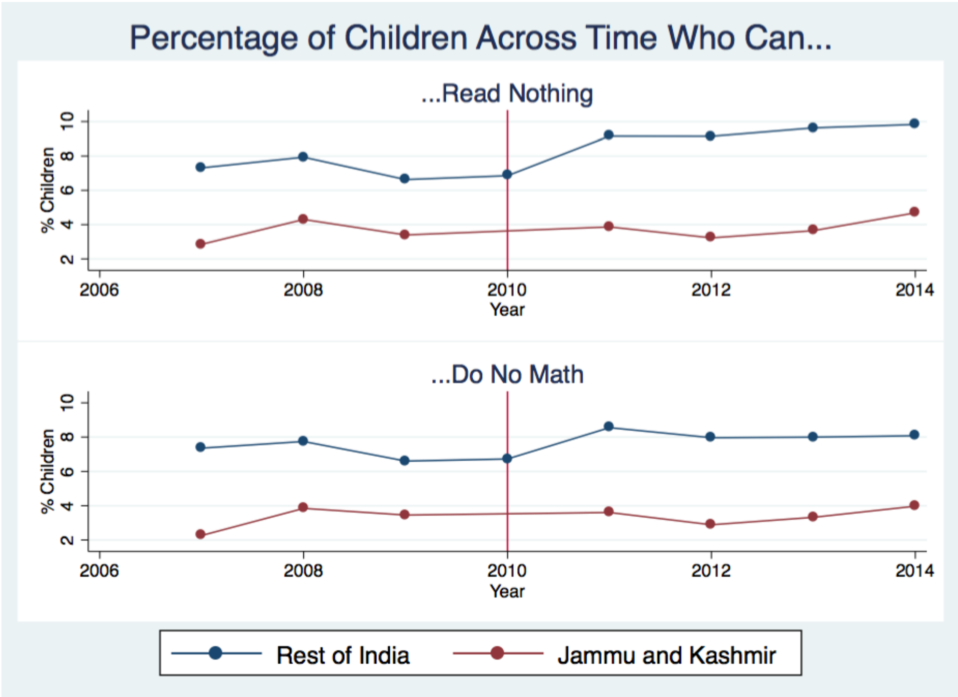
The regressions reveal that RTE shows some positive effects on language outcomes in grade 1, but consistently negative results in all the other grades in public schools. Table 9 indicates that RTE is associated with up to a 8 percentage point increase in likelihood that a student cannot read. RTE is also associated with a lower likelihood of having other language skills, such as the ability to read at least a paragraph (for instance in the third grade, being in a state under RTE results in approximately 3 percentage point lower likelihood of possessing that basic skill) and read stories. Going to a private school and being a male are associated with 6.9 and 0.4 percentage point increases respectively in the likelihood that a child can read.

The effects of RTE on math skills as seen in Table 10 are similar, though the results are less consistently statistically significant. While RTE is associated with small gains in the lower grades (such as an 8 percentage point increase in likelihood that a child can do division in grade 1), the results are broadly negative. For instance, a student in grade 2 is 3.2 percentage points less likely to be able to do any math at all and 5.1 percentage points less likely to be able to do at least subtraction. Going to a private school, on the other hand, is associated with a 5 to 13 percentage point increase in likelihood of having each of the math skills measured in this dataset. Male children are also more likely to be able to do any math at all, recognize two digit numbers, subtract and divide.

5.2. Robustness checks

Difference-in-differences assumes parallel pre-trends and the absence of omitted variables. To check whether the pre-trends are parallel, I plot the percentages of students with different literacy numeracy skills across time in the treatment and control groups.

Figure 1: Percentage of children across time with no language and math skills, treatment and control

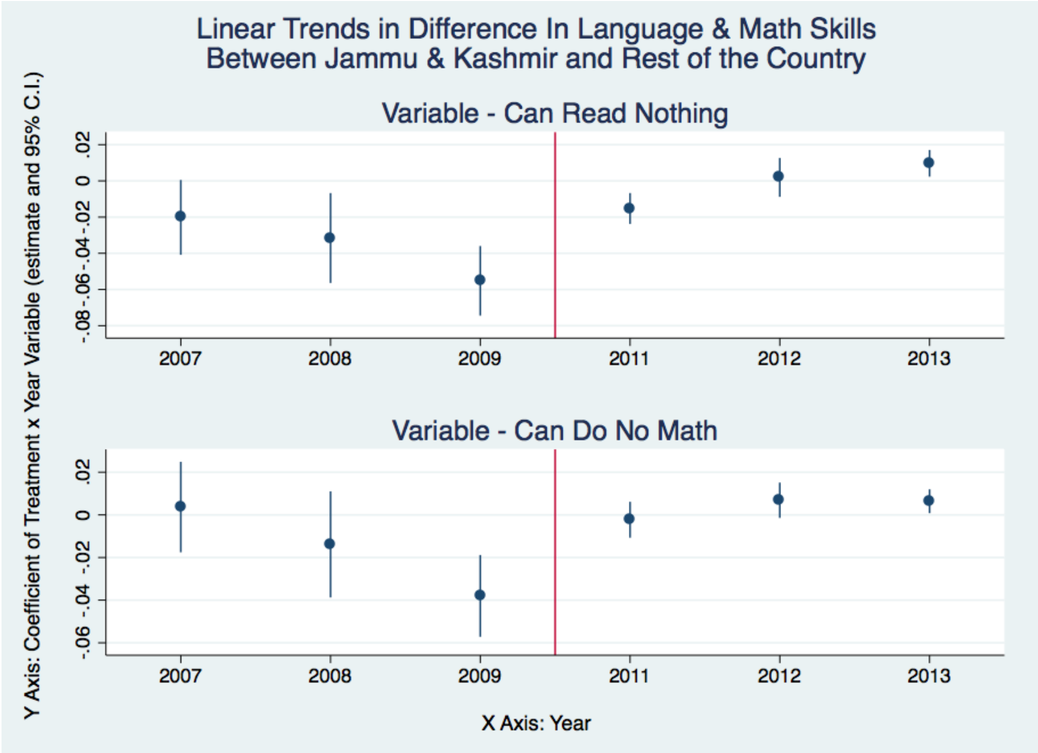


Source: Author's calculations using data from ASER.

From Figure 1, we can see that the percentages of students across time with no literacy and numeracy skills follow similar trends in Jammu and Kashmir (the control group) and the rest of India (treatment group) before 2010, and diverge after the introduction of RTE. However, eyeballing the difference is a highly imprecise way of checking for parallel pre-trends. Moreover, Figure 4 and Figure 5 in the appendix show that measures of other learning outcomes clearly violate the parallel pre-trends assumption.

To more rigorously check if the pre-trends are parallel, I interact the treatment dummy with each of the years in my sample and regress learning outcomes against these interaction variables.

Figure 2: Trends in differences in students with no math or language skills in Jammu and Kashmir vs. rest of the country



Source: Author's calculations using data from ASER.

As we can see from Figure 2, the 95% confidence intervals for the coefficients in the years preceding 2010 are not constant and do not include zero. Thus the pre-trends are not parallel, but there is a clear divergence post-2010. This is true for measures of other learning outcomes as well, as evidenced by Figures 6 and 7 in the appendix. Thus, the results of the traditional difference-in-differences regressions must be treated with extreme caution. For more reliable estimates of the effect of RTE on learning outcomes, I use a model that controls for differing pre-trends.

Table 3 shows the effects of RTE on language skills when we control for the different trends before 2010. Over and above existing trends, we see that the introduction of RTE is associated with a 2.6 percentage point increase in the likelihood that a student can read nothing at all, a 1.7 percentage point decrease in the likelihood that the student can read at least words and a 2.9 percentage point fall in the likelihood that the student can read a simple story. While only these measures are

Table 3: Trends-controlled estimates of RTE impact on likelihood of having language Skills – Jammu and Kashmir vs. rest of the country

Independent Variables	Dependent Variables				
	Can Read Nothing	Can Read At Least Letters	Can Read At Least Words	Can Read At Least A Paragraph	Can Read A Story
Treatment x Post-Time trend	0.0258***	-0.0050	-0.0168***	-0.0068	-0.0294***
	(0.0019)	(0.0045)	(0.0053)	(0.0055)	(0.0060)
Treatment x Time trend	-0.0151***	0.0025	0.0071	-0.0112***	0.0077*
	(0.0015)	(0.0039)	(0.0044)	(0.0040)	(0.0039)
Male dummy	-0.0042**	-0.0033**	0.0014	-0.0008	-0.0059
	(0.0016)	(0.0012)	(0.0038)	(0.0046)	(0.0054)
Private school	-0.0684***	0.0594***	0.1110***	0.1279***	0.1261***
	(0.0162)	(0.0177)	(0.0217)	(0.0207)	(0.0159)
Log GDP	0.0914	-0.1997	-0.2766	-0.2922	-0.3082*
	(0.0686)	(0.1485)	(0.1826)	(0.1812)	(0.1623)
R^2	0.17	0.14	0.30	0.35	0.31
N	2,900,124	2,900,124	2,900,124	2,900,124	2,900,124

Data is from ASER and Planning Commission of India. Regressions include state, year and grade fixed effects. Standard errors are clustered at the state level.

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table 4: Trends-controlled estimates of RTE impact on likelihood of having math skills – Jammu and Kashmir vs. rest of the country

Independent Variables	Dependent Variables				
	Can Do No Math	Can Recognize At Least 1-Digit Nrs	Can Recognize At Least 2-Digit Nrs	Can Do At Least Subtraction	Can Do Division
Treatment x Post-Time trend	0.0243***	-0.0069	-0.0474***	-0.0742***	-0.0497***
	(0.0018)	(0.0042)	(0.0054)	(0.0095)	(0.0088)
Treatment x Time trend	-0.0176***	0.0066*	0.0309***	0.0491***	0.0320***
	(0.0017)	(0.0037)	(0.0045)	(0.0057)	(0.0048)
Male dummy	-0.0058***	-0.0016	0.0147**	0.0155**	0.0157***
	(0.0018)	(0.0014)	(0.0055)	(0.0061)	(0.0054)
Private school	-0.0626***	0.0539***	0.1228***	0.1317***	0.1002***
	(0.0146)	(0.0159)	(0.0194)	(0.0153)	(0.0101)
Log GDP	0.0854	-0.1928	-0.3106	-0.3340	-0.3125
	(0.0708)	(0.1270)	(0.1839)	(0.2235)	(0.1877)
R^2	0.17	0.13	0.29	0.33	0.26
N	2,900,124	2,900,124	2,900,124	2,900,124	2,900,124

Data is from ASER and Planning Commission of India. Regressions include state, year and grade fixed effects. Standard errors are clustered at the state level.

* $p<0.1$; ** $p<0.05$; *** $p<0.01$.

statistically significant, estimates of the effect of RTE on other language skills are still negative. The standard errors, clustered at the state level, are very small. From Table 4, we see that RTE also has a consistent and statistically significant negative effect on math skills even when controlling for pre-existing trends.

A second robustness check limits the treatment group to Jammu and Kashmir's neighboring states in order to make the treatment and control groups more similar. Tables 11 and 12 in the appendix present the results of trends-controlled DID regressions on the limited sample. Once again, we see negative effects of RTE on the likelihood of a student being able to read at least words, read stories, recognize at least 2-digit numbers, do at least subtraction and do division. However, not all of these coefficients are statistically significant, and there is evidence of a small positive effect on the likelihood that students have the most basic literacy and numeracy skills (ability to recognize letters and 1-digit numbers).

5.3. Effect of RTE on school quality measures

To understand *why* RTE did not successfully improve learning outcomes, it is useful to consider the effect of the act on school characteristics. Table 5 presents the effects of treatment (being outside Jammu and Kashmir post 2010) on school quality measures (specifically, the percentage of teachers present and whether there is a usable blackboard in the 2^{nd} and 4^{th} grade classrooms). These regressions control for state and year fixed effects and logged GDP and cluster standard errors by state.

Teachers and school infrastructure have become more reliable under RTE. Since these variables do not follow parallel trends pre-2010 in the treatment and control groups (as seen Figure 11 in the appendix), I use the trends-controlled DID model specified in the "Methodology" section. From Table 5, we can see that RTE is associated with about a 2.4 percentage point increase in the likelihood of the school

Table 5: Trends-controlled DID estimates of RTE Impact on school characteristics, Jammu and Kashmir vs. rest of India

Independent Variables	Dependent Variables: Likelihood of Usable Blackboard in Grade 2	Likelihood of Usable Blackboard in Grade 4	Percentage of Teachers Present in School
Treatment x Post-Time trend	0.0247*** (0.0044)	0.0239*** (0.0051)	0.0170** (0.0071)
Treatment x Time trend	-0.0130*** (0.0039)	-0.0118** (0.0046)	-0.0052 (0.0067)
Log GDP	0.0666 (0.0962)	0.0829 (0.0948)	-0.0692 (0.0677)
R^2	0.02	0.03	0.03
N	96,695	84,936	79,331

Data is from ASER and Planning Commission of India. Regressions include state and year fixed effects. Standard errors are clustered at the state level.
* p<0.1; ** p<0.05; *** p<0.01.

having usable blackboards. These estimates are significant at the 1% significance level. Teacher absence improves and the change is statistically significant— the third column of Table 5 shows us that the percentage of teachers who are present at the school on the day of the survey is 1.7 percentage points higher under RTE. These improvements are seen under RTE despite controlling for differing pre-trends.

School-level regressions are also mostly robust to the second check of limiting the sample to just Jammu and Kashmir and its neighboring states, as seen in Table 13 in the appendix. The coefficients on whether schools have usable blackboards and the percentage of teachers who are at work are all still positive. However, the estimates are smaller; RTE is associated with a 0.1 percentage point increase in likelihood of having a usable blackboard in the 2nd grade classroom and a 2 percentage point increase in likelihood of having a usable blackboard in the 4th grade classroom. The coefficient on the percentage of teachers who showed up to work is no longer statistically significant even at the 10% level.

5.4. Channels for RTE effects on learning outcomes

In order to synthesize the above findings, the final set of regressions explores the relationship between school characteristics and learning outcomes. While these results do not have a causal interpretation, they can inform hypotheses about the channel through which RTE affects learning outcomes.

Tables 6 and 7 show that the percentage of students enrolled in school is associated with a positive and statistically significant effect (at the 1% level) on the percentage of students that have math and language skills. Specifically, a 1 percentage point increase in students enrolled in school is associated with 2.7 to 3.8 percentage point increases in the number of students who possess the various language skills measured. Similarly, a 1 percentage point increase in enrollment is associated with 2.4 to 3.8 percentage point increases in students with different math skills. However, the share of enrolled students in private schools, the percentage of schools with usable blackboards and the percentage of employed teachers present at work have no statistically significant effect on learning outcomes. The changes in learning outcomes are not caused by increases in wealth, since I control for logged GDP.

Tables 14 and 15 in the appendix show the results of these regressions when including lagged versions of the variables. Current student enrollment is the only variable that is consistently associated with a statistically significant change in learning outcomes. These estimates are also almost unchanged from the previous set of regressions. Once again, these regressions control for logged GDP and include year- and state-fixed effects.

Table 6: Predictors of percentage of public school students with language skills in a state

Independent Variables	Dependent Variables				
	Can Read Nothing	Can Read At Least Letters	Can Read At Least Words	Can Read At Least Paragraphs	Can Read Stories
Percentage of students enrolled	-1.1143***	2.7250***	3.8342***	3.8435***	3.2564***
	(0.2052)	(0.3774)	(0.4196)	(0.3355)	(0.3876)
Percentage of enrolled students in private schools	-0.0224	0.0476	-0.0350	-0.0671	-0.0250
	(0.0164)	(0.0460)	(0.0558)	(0.0655)	(0.0663)
Percentage of schools with usable blackboard in grade 2	-0.0387	-0.3447	-0.5086	-0.6682	-0.7441
	(0.1358)	(0.2714)	(0.3177)	(0.4726)	(0.6461)
Average percentage of teachers present	0.0623	0.0286	-0.0645	-0.2257	-0.3803
	(0.0762)	(0.0999)	(0.1493)	(0.2003)	(0.2289)
Log GDP	0.0107***	-0.0097*	-0.0099	0.0036	0.0185***
	(0.0035)	(0.0054)	(0.0064)	(0.0054)	(0.0054)
R^2	0.73	0.82	0.82	0.76	0.62
N	122	122	122	122	122

Data is from ASER and Planning Commission of India. Regressions include state and year fixed effects. Standard errors are clustered at the state level.

* $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Table 7: Predictors of percentage of public school students with math skills in a state

Independent Variables	Dependent Variables				
	Can Do No Math	Can At Least Recognize 1-Digit Nrs	Can At Least Recognize 2-Digit Nrs	Can Do At Least Subtraction	Can Do Division
Percentage of students enrolled	-1.0225 (0.1464)***	2.5952 (0.3757)***	3.6182 (0.4029)***	3.7613 (0.3973)***	2.3921 (0.3522)***
Percentage of enrolled students in private schools	-0.0126 (0.0130)	0.0337 (0.0430)	-0.0011 (0.0574)	-0.1128 (0.0678)	-0.0901 (0.0630)
Percentage of schools with usable blackboard in grade 2	-0.0816 (0.1142)	-0.2770 (0.2154)	-0.2516 (0.3426)	-0.5131 (0.5479)	-0.5400 (0.6003)
Average percentage of teachers present	0.0525 (0.0619)	0.0395 (0.0925)	-0.0152 (0.1489)	-0.0938 (0.2041)	-0.1609 (0.2004)
Log GDP	0.0085 (0.0025)***	-0.0078 (0.0047)	-0.0205 (0.0070)***	-0.0074 (0.0078)	0.0033 (0.0063)
R^2	0.72	0.81	0.83	0.74	0.56
N	122	122	122	122	122

Data is from ASER and Planning Commission of India. Regressions include state and year fixed effects. Standard errors are clustered at the state level.

* $p<0.1$; ** $p<0.05$; *** $p<0.01$.

6. Discussion

RTE was a much-celebrated constitutional amendment attempting to create a universal right to education, but the above results make it clear that it has not improved literacy and numeracy skills. The difference-in-differences regressions show that RTE actively worsened learning measures across grades. At best, being very conservative in interpreting the robustness checks, the effect of RTE on learning outcomes is not statistically significantly different from zero for almost any language and math skills across grade levels. On the other hand, RTE has resulted in an improvement in school infrastructure and teacher absence.

Naturally, there are many omitted variables that could have caused my results and so these findings must be treated with caution until corroborated by other researchers. State fixed effects control for state-specific characteristics invariant across a 7-year-period such as geography. Year fixed effects control for other policy changes that may have affected all of India. Controlling for GDP suggests that changes in income are not driving the result either. I do not control for education spending overall because RTE includes financial transfers from the central government to the state government and therefore evaluating RTE includes evaluating the effectiveness of these endogenous transfers. However, to ensure the reliability of these findings, future research should investigate other policies that may have had an effect on education and also try to control for student-level characteristics such as income and readiness for school.

In this section, assuming that my results are robust, I describe and evaluate possible explanations for why RTE caused them. Since I cannot link school characteristics to specific students in my dataset, these explanations do not conclusively prove causation. Instead, I use results from the OLS regressions of state-level enrollment and school quality measures on learning outcomes to support my argument. I also point out evidence from the education economics literature that could help us understand these results and point out opportunities for future research.

6.1. Has RTE not been implemented by states?

The most basic explanation for why RTE did not have a positive impact on learning outcomes could be that the Act, despite its enactment at the federal level, was not implemented by the states. However, there are a couple of issues with this explanation. If this is indeed true, it should be serious cause for concern that a constitutional amendment enacted in 2010 has not been implemented by states even four years later. Moreover, a lack of implementation cannot explain the negative impact found in the difference-in-differences analysis. This is especially true when the treatment group in the regressions is limited to the neighboring states of Punjab and Himachal Pradesh, because both of these states filed a detailed plan for implementation (Punjab RTE Rules (2011), Himachal Pradesh RTE Rules (2011)). Lack of implementation is, hence, unlikely to be the reason for the fall in learning outcomes.

6.2. Has RTE resulted in more unprepared students going to school?

A second possible explanation is that the RTE has been implemented and is actually effective in causing more students to go to school, and that this entrance of new and underprepared students causes a fall in learning outcomes. As an analogy, average test scores in the United States of America would almost certainly rise if families earning less than $40,000 stopped sending their kids to public school, but this would not be a desirable outcome for any policymaker or concerned citizen[11].

However, the OLS regressions of learning outcomes against state-level education characteristics show that an increase in enrollment is correlated with a rise, and not a fall, in learning outcomes (see Tables 6 and 7 above for the general regressions and Tables 14 and 15 in the appendix for a version with lagged variables). Reverse causality could mean that better schools cause more students to enroll in them. Hence I also run a version of the regression controlling for enrollment in the previous year. Increased enrollment in year $n - 1$ does have a negative effect on most learning outcomes in year n, but none of these coefficients are statistically significant even at the 10% level. Thus it appears unlikely that just increased enrollment is driving the results.

The dramatic rise in private schools in this time period across India (ASER 2014) could have drawn more skilled students away from public schools, leaving worse students behind. This would result in worse learning outcome measures. To check this hypothesis, the OLS regressions control for the percentage of enrolled students in private schools in each state according to the ASER data. However, an increase in the share of students going to private schools is not associated with a statistically significant change in learning outcomes in either the current or the next year, and so the rise of private schools also does not appear to be causing the decline of the quality of public education in India.

6.3. Has RTE strained school resources?

If RTE increased enrollment, this could strain the resources of existing schools. This could take the form of high pupil-teacher ratios, fewer textbooks per

[11] Thanks to Nathaniel Donahue for suggesting the analogy.

child, or overused classrooms. If learning outcomes are heavily dependent on the quality and quantity of inputs, we would see a fall in learning outcomes over time. However, the school regression results in Table 5 show that school infrastructure and teacher absence have both improved under RTE as well. This is consistent with other research on the quality of public schools in India. Muralidharan et al. (2017) visit public schools in rural India in 2003 and 2010, collecting data on a variety of characteristics. They find large increases in the fraction of schools with functioning toilets, electricity, libraries and drinking water. They also see a fall in teacher absence from 26.3% of teachers to 23.6%.

Moreover, my OLS regressions find that improved infrastructure (using the percentage of schools with a usable blackboard in grade 2 as a proxy) and teacher attendance have no statistically significant association with learning outcomes. While this may seem counterintuitive, a series of studies in India and other developing countries have found that improvement in inputs has a negligible effect on learning outcomes. Muralidharan et al. (2017) shows using a nationally representative sample of over a thousand village schools that there is no correlation between changes in school infrastructure and student test scores. Borkum, He and Linden (2013) experimentally find over five years that a school-library program has no effect on student test measures.

Despite the literature showing negligible impact of inputs on learning outcomes, RTE focuses on improving infrastructure and pupil-teacher ratios. The focus on improving educational inputs, as opposed to improving learning measures, is a consistent problem in Indian education policy. As Muralidharan (2013) points out there is “no mention of learning outcomes” in the document laying out the goals of India’s Ministry of Human Resource Development for 2012-13. This suggests that the government of India requires a radical rethinking of the input-based approach it has followed for so long. The RTE act has been successful at improving school infrastructure, teacher absence and student attendance rates, but has had either no or negative effect on learning outcomes. Instead, learning outcomes may be driven by unseen variables such as the quality of teaching, the pedagogical methods used, and the curriculum. This is an important avenue for future research and the effect of these unseen variables can be measured through a randomized control trial, or by exploiting other natural experiments like the one used in this paper.

7. Conclusion

This paper uses comprehensive data on learning outcomes and school infrastructure from the Annual Status of Education Report surveys to measure the causal effect of the Right to Education Act. I find that school infrastructure and teacher attendance have improved. However, students do not show improved levels of language and math skills and there is even evidence of a negative effect. I suggest that this could be due to unmeasured variables such as the quality of teachers, curricula or pedagogical methods that RTE and other Indian educational policies have not focused on.

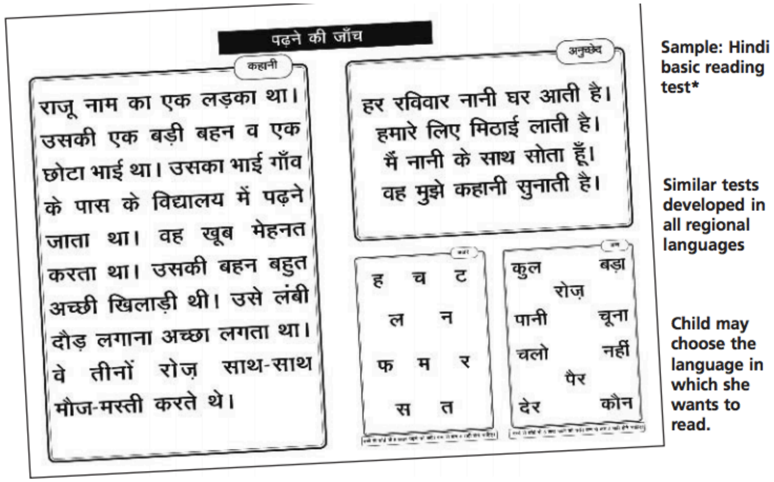
This does not conclusively prove that RTE has failed. Omitted variables that I could not control for may make the state of Jammu and Kashmir an unsatisfactory control group. Six years may be too short a time to see the full impact of RTE, and future research should include data from more years. RTE also comprises many different rules that regulate pupil-teacher ratios, infrastructure, education spending and private school enrollment. Even if my findings are robust, some of these provisions may have a positive impact and this paper cannot separate their effects.

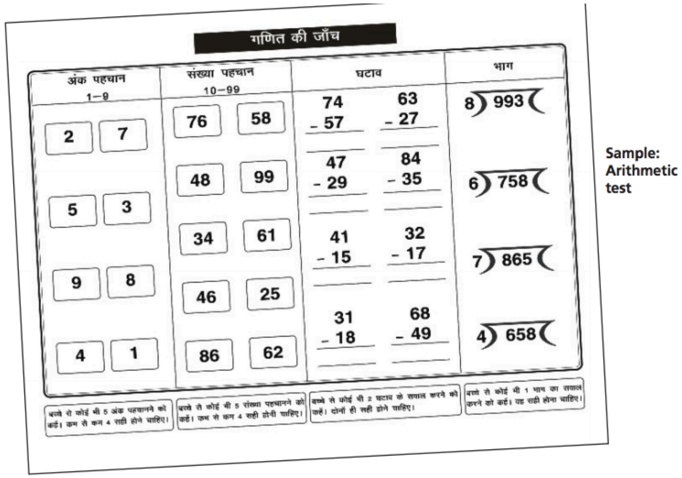
Nevertheless, RTE has evidently not lived up to its aspirational rhetoric and has not succeeded in ensuring access to "the skills, knowledge, values and attitudes necessary to become responsible and active citizens of India[12]". If RTE's impotence is indeed driven by fundamental issues with India's education policy, it could encourage changes such as making improving learning outcomes an "explicit goal of primary education policy," curricular reform, and changes in school governance (Muralidharan 2013). It is clear that the government of India can follow through on ambitious goals like improving school infrastructure across the country— it may simply be a question of better defining the variables that they are optimizing for.

[12] "PM's Address on Fundamental Right of Children to Elementary Education." 2010. https://tinyurl.com/hindu-rte

Appendix

Figure 3: Sample language and math tests adminstered to children





Source: ASER 2014

Table 8: List of states and union territories for which I have data on both GDP and learning outcomes

Andhra Pradesh	Goa	Jharkhand	Manipur	Puducherry	Tripura
Arunchal Pradesh	Gujarat	Karnataka	Meghalaya	Punjab	Uttar Pradesh
Assam	Haryana	Kerala	Mizoram	Rajasthan	Uttarakhand
Bihar	Himachal Pradesh	Madhya Pradesh	Nagaland	Sikkim	West Bengal
Chhattisgarh	Jammu and Kashmir	Maharashtra	Odisha	Tamil Nadu	

Table 9: DID estimate of RTE impact on likelihood that student has language skills: Jammu and Kashmir vs. rest of the country

Variables	Can Read Nothing	Can Read At Least Letters	Can Read At Least Words	Can Read At Least A Paragraph	Can Read A Story
Post-RTE x Treatment group	-0.0107*	0.0221	-0.0063	-0.1109***	-0.1549***
	(0.0062)	(0.0141)	(0.0160)	(0.0142)	(0.0188)
Treatment x Grade 1	0.0802**	-0.0623**	0.0682***	0.1349***	0.1555***
	(0.0296)	(0.0301)	(0.0180)	(0.0179)	(0.0281)
Treatment x Grade 2	0.0738***	-0.0560***	-0.0325	0.0989***	0.1542***
	(0.0156)	(0.0156)	(0.0281)	(0.0152)	(0.0274)
Treatment x Grade 3	0.0490***	-0.0343***	-0.0654**	0.0151	0.1289***
	(0.0093)	(0.0101)	(0.0263)	(0.0318)	(0.0182)
Treatment x Grade 4	0.0309***	-0.0158**	-0.0561***	-0.0283	0.0726***
	(0.0053)	(0.0062)	(0.0175)	(0.0265)	(0.0171)
Treatment x Grade 5	0.0201***	-0.0066	-0.0364***	-0.0311	0.0254
	(0.0036)	(0.0041)	(0.0106)	(0.0197)	(0.0198)
Treatment x Grade 6	0.0084***	0.0004	-0.0176***	-0.0198	0.0070
	(0.0014)	(0.0021)	(0.0061)	(0.0118)	(0.0144)
Treatment x Grade 7	0.0026***	0.0026	-0.0036	-0.0058	0.0061
	(0.0009)	(0.0016)	(0.0029)	(0.0049)	(0.0065)
Private school	-0.0690***	0.0599***	0.1115***	0.1274***	0.1248***
	(0.0163)	(0.0177)	(0.0218)	(0.0206)	(0.0158)
Male dummy	-0.0045**	-0.0031**	0.0013	-0.0011	-0.0063
	(0.0016)	(0.0013)	(0.0038)	(0.0045)	(0.0053)
Log GDP	0.0882	-0.2000	-0.2769	-0.2920	-0.3094*
	(0.0671)	(0.1454)	(0.1835)	(0.1824)	(0.1625)
R^2	0.18	0.15	0.30	0.36	0.32
N	2,900,124	2,900,124	2,900,124	2,900,124	2,900,124

Data is from ASER and Planning Commission of India. Regressions include state, year and grade fixed effects. Standard errors are clustered at the state level.

* p<0.1; ** p<0.05; *** p<0.01

Table 10: DID estimator of RTE impact on likelihood that student has math skills - Jammu and Kashmir vs. rest of the country

Variables	Can Do No Math	Can Recognize At Least 1-Digit Nrs	Can Recognize At Least 2-Digit Nrs	Can Do At Least Subtraction	Can Do Division
Post-RTE x Treatment group	-0.0108*	0.0157	-0.0139	-0.0982***	-0.1559***
	(0.0057)	(0.0118)	(0.0163)	(0.0238)	(0.0340)
Treatment x Grade 1	0.0531*	-0.0321	0.0688***	0.1979***	0.2386***
	(0.0310)	(0.0320)	(0.0199)	(0.0274)	(0.0427)
Treatment x Grade 2	0.0427**	-0.0239	-0.0235	0.1495***	0.2250***
	(0.0159)	(0.0161)	(0.0293)	(0.0237)	(0.0420)
Treatment x Grade 3	0.0260***	-0.0105	-0.0631**	0.0527*	0.1932***
	(0.0083)	(0.0090)	(0.0282)	(0.0296)	(0.0333)
Treatment x Grade 4	0.0161***	-0.0005	-0.0536***	0.0063	0.1319***
	(0.0046)	(0.0057)	(0.0192)	(0.0282)	(0.0222)
Treatment x Grade 5	0.0112***	0.0028	-0.0385***	-0.0075	0.0802***
	(0.0027)	(0.0031)	(0.0113)	(0.0221)	(0.0180)
Treatment x Grade 6	0.0036***	0.0052**	-0.0176**	-0.0076	0.0389***
	(0.0010)	(0.0019)	(0.0069)	(0.0136)	(0.0131)
Treatment x Grade 7	0.0012	0.0045***	-0.0047	-0.0031	0.0200***
	(0.0008)	(0.0016)	(0.0035)	(0.0066)	(0.0061)
Private school	-0.0629***	0.0541***	0.1232***	0.1307***	0.0983***
	(0.0146)	(0.0159)	(0.0194)	(0.0151)	(0.0100)
Male dummy	-0.0059***	-0.0015	0.0147**	0.0150**	0.0151***
	(0.0018)	(0.0014)	(0.0054)	(0.0060)	(0.0053)
Log GDP	0.0821	-0.1926	-0.3077	-0.3340	-0.3173*
	(0.0724)	(0.1258)	(0.1840)	(0.2208)	(0.1827)
R^2	0.17	0.13	0.29	0.33	0.27
N	2,900,124	2,900,124	2,900,124	2,900,124	2,900,124

Data is from ASER and Planning Commission of India. Regressions include state, year and grade fixed effects. Standard errors are clustered at the state level.

* p<0.1; ** p<0.05; *** p<0.01

Figure 4: Percentage of children across time with different language skills, Jammu and Kashmir vs. rest of the country

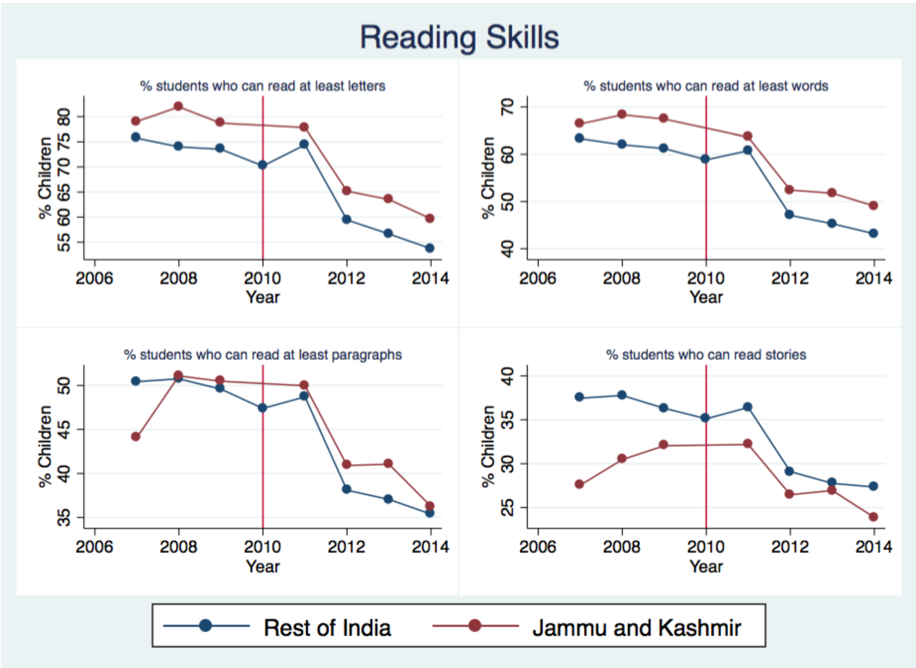


Figure 5: Percentage of children across time with different language skills, Jammu and Kashmir vs. rest of the country

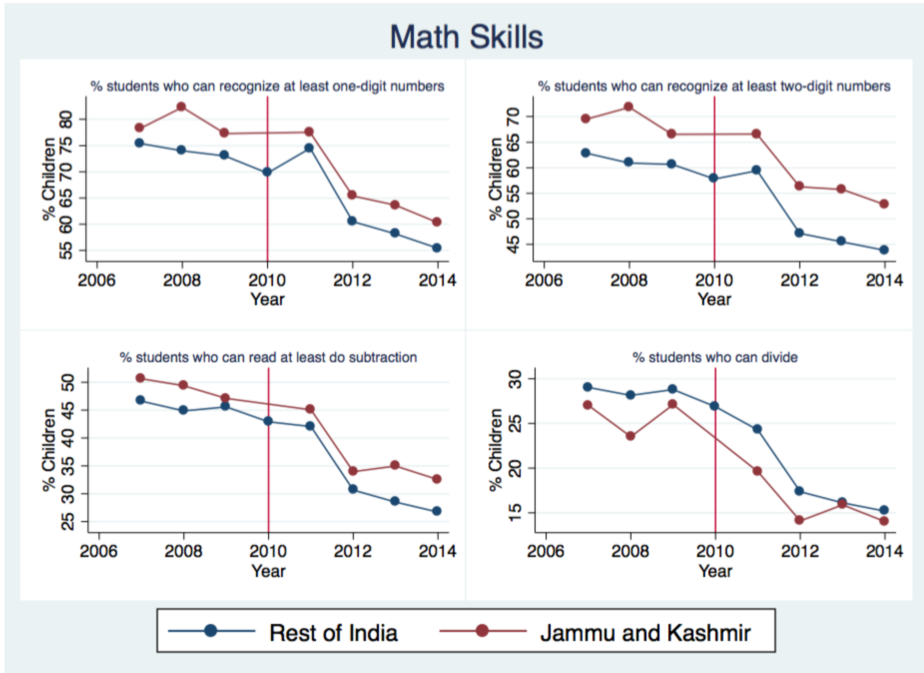


Figure 6: Trends in differences in language skills in Jammu and Kashmir vs. rest of the country

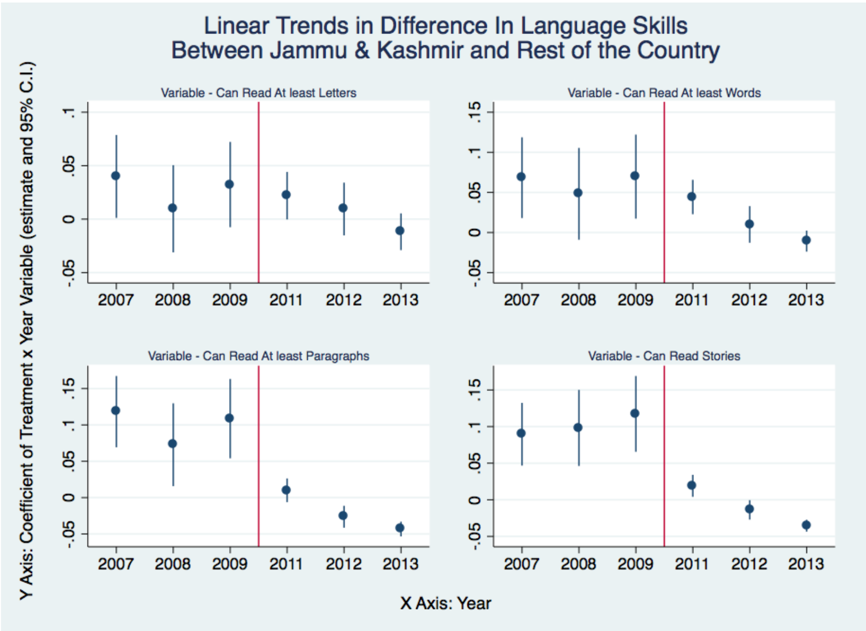


Figure 7: Trends in differences in math skills in Jammu and Kashmir vs. rest of the country

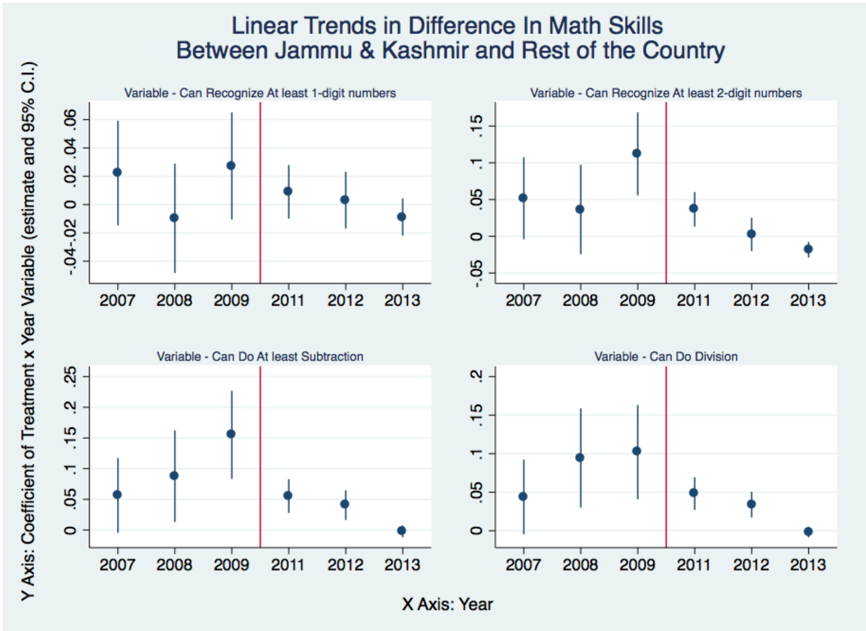


Figure 8: Trends in differences in language and math skills in Jammu and Kashmir vs. neighboring states

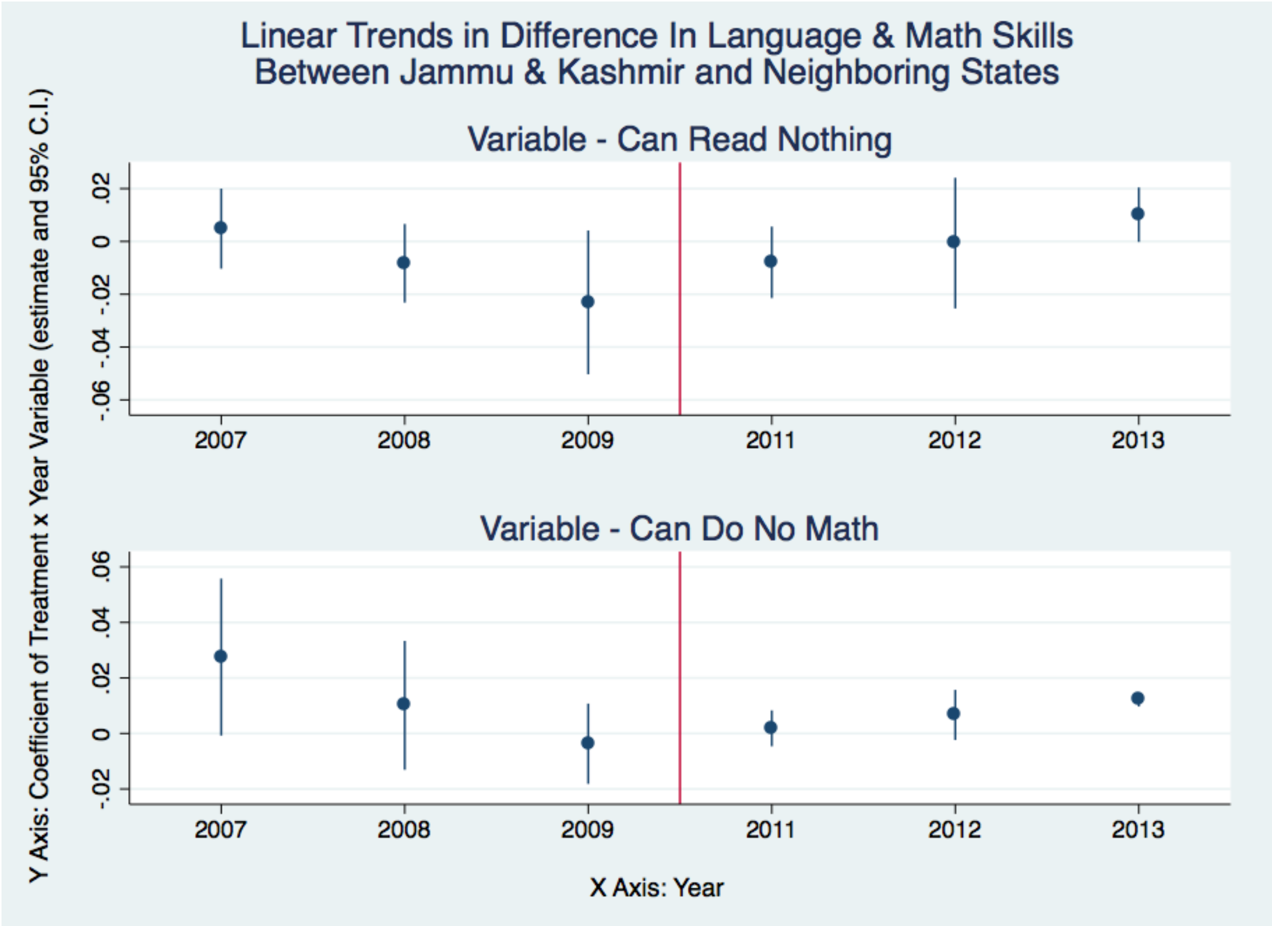


Figure 9: Trends in differences in language skills in Jammu and Kashmir vs. neighboring states

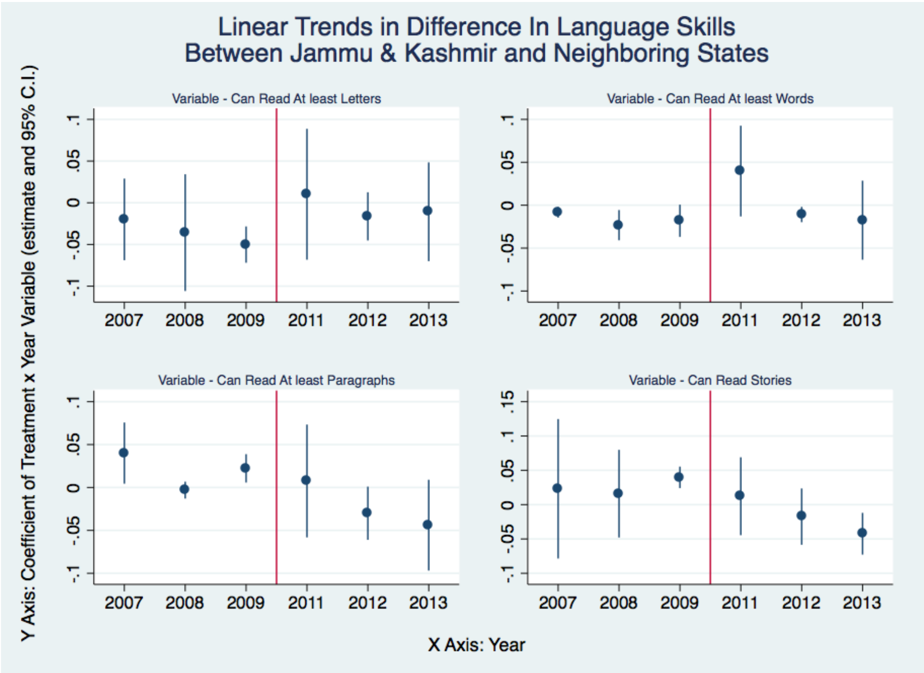


Figure 10: Trends in differences in math skills in Jammu and Kashmir vs. neighboring states

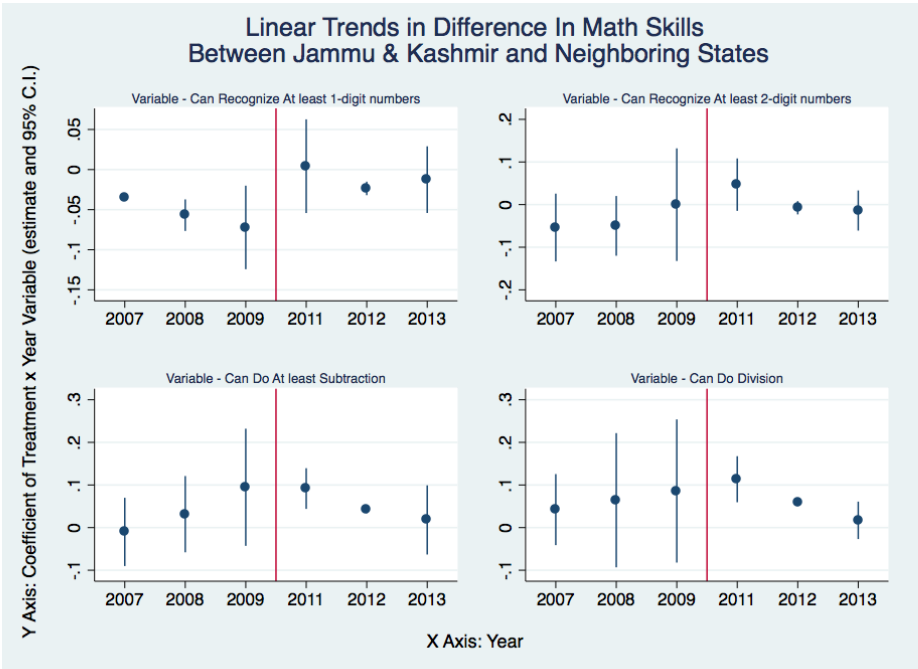


Table 11: Trends-controlled DID estimator of RTE impact on likelihood of language Skills - JK vs. neighboring states

Independent Variables	Dependent Variables				
	Can Read Nothing	Can Read At Least Letters	Can Read At Least Words	Can Read At Least A Paragraph	Can Read A Story
Treatment x Post-Time trend	0.0180**	0.0181***	-0.0030	0.0008	-0.0222
	(0.0024)	(0.0016)	(0.0020)	(0.0056)	(0.0156)
Treatment x Time trend	-0.0119**	-0.0112**	0.0044	-0.0043	0.0161
	(0.0017)	(0.0020)	(0.0025)	(0.0039)	(0.0117)
Male dummy	0.0015	-0.0097	-0.0177	-0.0218	-0.0307
	(0.0021)	(0.0048)	(0.0102)	(0.0119)	(0.0162)
Private school	-0.0324***	0.0238**	0.0947**	0.1203	0.1107
	(0.0031)	(0.0048)	(0.0203)	(0.0437)	(0.0422)
Log GDP	-0.0460**	0.2442	0.0140	-0.4142***	-0.7049***
	(0.0097)	(0.1063)	(0.1477)	(0.0375)	(0.0686)
R^2	0.09	0.06	0.24	0.33	0.32
N	195,192	195,192	195,192	195,192	195,192

Data is from ASER and Planning Commission of India. Regressions include state, year and grade fixed effects. Standard errors are clustered at the state level.

* *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table 12: Trends-controlled DID estimates of RTE impact on likelihood of math skills - JK vs. neighboring states

Independent Variables	Dependent Variables				
	Can Do No Math	Can Recognize At Least 1-Digit Nrs	Can Recognize At Least 2-Digit Nrs	Can Do At Least Subtraction	Can Do Division
Treatment x Post-Time trend	0.0177***	0.0225**	-0.0425**	-0.0855***	-0.0614**
	(0.0016)	(0.0047)	(0.0051)	(0.0062)	(0.0102)
Treatment x Time trend	-0.0169***	-0.0088	0.0465**	0.0726***	0.0499**
	(0.0013)	(0.0042)	(0.0050)	(0.0053)	(0.0090)
Male dummy	-0.0004	-0.0081	-0.0093	-0.0089	-0.0059
	(0.0020)	(0.0048)	(0.0064)	(0.0118)	(0.0134)
Private school	-0.0308***	0.0227**	0.1001***	0.1361**	0.0944*
	(0.0027)	(0.0029)	(0.0057)	(0.0294)	(0.0256)
Log GDP	0.1560***	-0.0465	-0.6990*	-0.8686**	-0.9951*
	(0.0139)	(0.1461)	(0.1903)	(0.1791)	(0.2757)
R^2	0.08	0.05	0.19	0.30	0.27
N	195,192	195,192	195,192	195,192	195,192

Data is from ASER and Planning Commission of India. Regressions include state, year and grade fixed effects. Standard errors are clustered at the state level.

* p<0.1; ** p<0.05; *** p<0.01

Figure 11: Trends in differences in school characteristics in Jammu and Kashmir and rest of the country

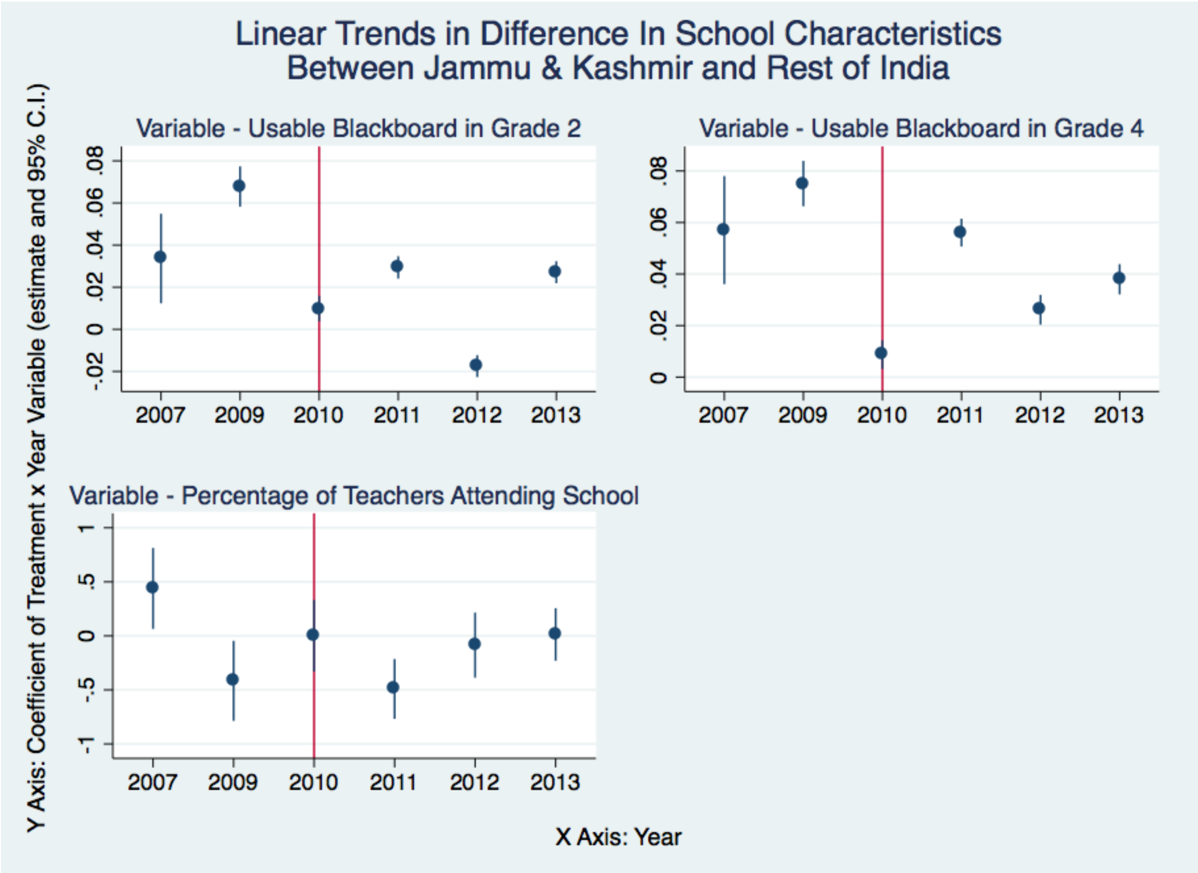


Figure 12: Trends in differences in school characteristics in Jammu and Kashmir and neighboring states

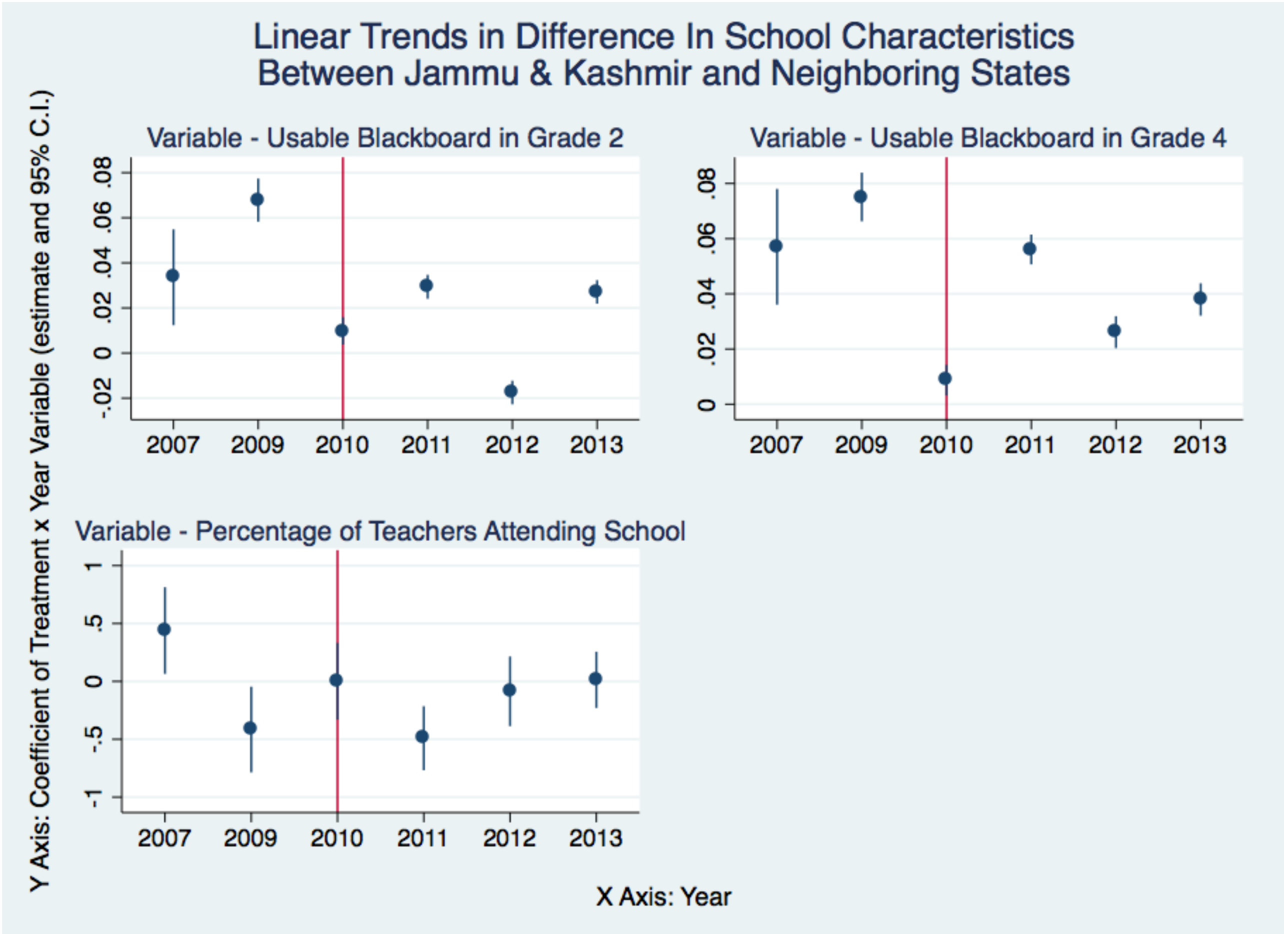


Table 13: Trends-controlled DID estimator of RTE impact on school characteristics, JK vs neighboring states

Independent Variables	Dependent Variables		
	Likelihood of Usable Blackboard in Grade 2	Likelihood of Usable Blackboard in Grade 4	Percentage of Teachers Present in School
Treatment x Post-Time trend	0.0117***	0.0212*	0.0111
	(0.0010)	(0.0065)	(0.0144)
Treatment x Time trend	-0.0066***	-0.0118	0.0041
	(0.0006)	(0.0051)	(0.0107)
Log GDP	0.3462***	0.2428**	-0.6524*
	(0.0241)	(0.0423)	(0.2185)
R^2	0.01	0.02	0.01
N	6,952	6,092	6,514

Data is from ASER and Planning Commission of India. Regressions include state, year and grade fixed effects. Standard errors are clustered at the state level.

* p<0.1; ** p<0.05; *** p<0.01

Table 14: Predictors of percentage of students with language skills in a state (lagged variables)

Variables	Can Read Nothing	Can Read At Least Letters	Can Read At Least Words	Can Read At Least Paragraphs	Can Read Stories
Percentage of students enrolled	-0.8906***	2.4210***	3.6481***	3.7973***	3.2506***
	(0.2156)	(0.4342)	(0.5082)	(0.4828)	(0.5230)
Percentage of enrolled students in private schools	0.0124	0.0421	-0.0730	-0.1146*	-0.0756
	(0.0201)	(0.0446)	(0.0624)	(0.0661)	(0.0610)
Percentage of schools with usable blackboard in grade 2	-0.1600	-0.2847	-0.5180	-0.7421	-0.9048
	(0.2029)	(0.2900)	(0.4897)	(0.7043)	(0.7937)
Average percentage of teachers present	0.0778	-0.0813	-0.1599	-0.2303	-0.3026
	(0.0811)	(0.1359)	(0.1733)	(0.2419)	(0.2892)
Lagged % enrolled	-0.5113**	-0.1165	-0.0284	-0.1045	-0.1998
	(0.2206)	(0.4014)	(0.4784)	(0.6005)	(0.6466)
Lagged % of enrolled in private schools	0.0384	0.0069	-0.0239	-0.0413	-0.0369
	(0.0303)	(0.0436)	(0.0657)	(0.0876)	(0.0988)
Lagged % of schools with usable blackboard in grade 2	0.0686	-0.0034	0.2484	0.5045	0.7431
	(0.1505)	(0.2409)	(0.3860)	(0.4870)	(0.6065)
Lagged average % of teachers present	0.0001	-0.2157*	-0.0824	0.0694	0.0971
	(0.1320)	(0.1056)	(0.1733)	(0.2146)	(0.3049)
Log GDP	0.0098**	-0.0130***	-0.0107	0.0059	0.0228**
	(0.0037)	(0.0045)	(0.0075)	(0.0088)	(0.0102)
R^2	0.81	0.86	0.85	0.79	0.65
N	94	94	94	94	94

Data is from ASER and Planning Commission of India. Regressions include state and year fixed effects. Standard errors are clustered at the state level.

* p<0.1; ** p<0.05; *** p<0.01

Table 15: Predictors of percentage of students with math skills in a state (lagged variables)

Variables	Can Do No Math	Can At Least Recognize 1-Digit Nrs	Can At Least Recognize 2-Digit Nrs	Can Do At Least Subtraction	Can Do Division
Percentage of students enrolled	-0.9058***	2.4053***	3.2805***	3.5387***	2.2926***
	(0.1544)	(0.4375)	(0.5018)	(0.6002)	(0.5128)
Percentage of enrolled students in private schools	0.0153	0.0350	-0.0289	-0.1589**	-0.1376**
	(0.0161)	(0.0428)	(0.0552)	(0.0726)	(0.0587)
Percentage of schools with usable blackboard in grade 2	-0.1311	-0.2604	-0.8359	-1.3119	-0.9629
	(0.1909)	(0.2748)	(0.5363)	(0.8234)	(0.8511)
Average percentage of teachers present	0.0678	-0.0733	-0.1113	-0.0866	-0.0726
	(0.0789)	(0.1316)	(0.1942)	(0.2529)	(0.2530)
Lagged % enrolled	-0.4596**	-0.2111	0.7330	0.4140	-0.0052
	(0.2212)	(0.3997)	(0.5792)	(0.6506)	(0.6242)
Lagged % of enrolled in private schools	0.0352	0.0065	0.0256	0.0283	-0.0015
	(0.0260)	(0.0437)	(0.0774)	(0.1132)	(0.1150)
Lagged % of schools with usable blackboard in grade 2	0.0700	-0.0004	-0.3031	0.0075	0.3119
	(0.1665)	(0.2529)	(0.4367)	(0.5391)	(0.5707)
Lagged average % of teachers present	0.0110	-0.2432**	-0.2920	-0.1268	0.0236
	(0.0986)	(0.1019)	(0.1892)	(0.2324)	(0.2352)
Log GDP	0.0077**	-0.0111**	-0.0222***	-0.0080	0.0033
	(0.0034)	(0.0044)	(0.0078)	(0.0107)	(0.0109)
R^2	0.80	0.84	0.87	0.79	0.61
N	94	94	94	94	94

Data is from ASER and Planning Commission of India. Regressions include state, year and grade fixed effects. Standard errors are clustered at the state level.

* p<0.1; ** p<0.05; *** p<0.01

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