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Learning Outlines and Teacher Training: A Difference-in-Differences Evaluation of Pratham Government Partnerships in India

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Honors Thesis

LEARNING OUTCOMES AND TEACHER TRAINING: A DIFFERENCE-IN-DIFFERENCES EVALUATION OF PRATHAM GOVERNMENT PARTNERSHIPS IN INDIA

by
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ABSTRACT

LEARNING OUTCOMES AND TEACHER TRAINING: A DIFFERENCE-IN-DIFFERENCES EVALUATION OF PRATHAM GOVERNMENT PARTNERSHIPS IN INDIA

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Bachelor of Science

India is working to improve learning in primary schools. In this paper, I evaluate the impact of partnerships between Pratham, an education-centered NGO, and Indian government schools. Using a difference-in-differences design to examine the impact of the partnership in Uttar Pradesh, I find a positive short-run effect (a 7% increase in test scores) using state-wide ASER data, and I find inconclusive effects using data restricted to government schools. Considering channels through which the partnerships may impact student learning, I conclude that the program shows potential to have positive, longer-term effects.

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I. Introduction

India's 2019 Draft Education Policy calls for foundational literacy and numeracy for all children by 2025. While ongoing efforts to improve education in India have led to an increase in student enrollment for children ages 6 to 14—which has been above 95% since 2007 and recently surpassed 97% —Indian school systems are still working to improve learning. As a result, NGOs, school districts, and researchers in India are experimenting with different forms of learning-focused educational interventions in government schools.

Pratham—a large, education-focused NGO—leads many of these initiatives. The organization's mission, "Every child in school and learning well," emphasizes both enrollment and achievement. Thus, Pratham works with government schools throughout India to train teachers and implement interventions that aim to bolster community support for education. Pratham recently initiated a series of government partnerships with state governments and school districts. These partnerships include teacher trainings and on-site support for instructors. They were implemented at the state and district levels in select states throughout India, beginning in 2016. Researchers currently monitor the effectiveness of Pratham's partnerships by using student test scores collected before and after the interventions. However, without a clear counterfactual outcome for schools that participate in the partnerships, it is difficult to attribute changes in scores to the Pratham programs. Because understanding the impact of Pratham's government partnerships will allow the organization to adapt future efforts to student needs and help India reach its educational aims, in this paper I analyze the causal impact of Pratham government partnerships on student achievement using a difference-in-differences methodology.

Various researchers have examined Pratham's previous programs, finding mixed results across different types of interventions. The majority of these assessments are from randomized control trials. For example, He et. al (2008) partnered with the Pratham English Language Education Program to analyze the effect of a technology-aided instruction program by randomly varying which students participated in teacher-led flashcard activities and which used interactive learning software. They found that higher performing students benefitted more from self-paced machine intervention, while lower performing students benefitted more from teacher help. Similarly, Banerjee et. al (2010) discovered that giving children computer time increased math scores by randomly assigning children to play math-related computer games.

Experimental research with Pratham has also guided the design of the partnerships studied in this paper. Banerjee et al. (2016) designed an experiment to study the effects of Pratham-supported teacher training in Haryana. In addition, they implemented 40-day learning camps in Uttar Pradesh to test the impact of instruction based on student achievement level rather than grade level. Both revealed positive effects on student test scores, garnering support for Pratham's government partnerships. However, this paper presents the first causal analysis of the partnerships themselves. Because the partnerships are implemented at the state or district level, they are not executed as part of randomized control trials. Hence, in contrast to previous Pratham-based research, I will seek pre-existing counterfactuals to analyze the impact of the intervention.

Although the Pratham-specific literature does not evaluate government-level partnerships, there is a large body of existing research on government-run schools and teacher preparation in India. Bhatt (2007) provides a comprehensive review, explaining that critics of the Indian education system cite lack of resources, scarcity of teachers, and teacher absenteeism among reasons for low achievement. More specifically, Muralidharan et al. (2013) exposed inefficiencies in government teacher-training by using experimental evidence to highlight benefits of contract teachers who received no professional training. Research focusing on comparisons between private and public schools yields mixed results. Some researchers suggest that private schooling provides significant educational achievement advantages (French et al. 2014). Others use experimental results to argue that the difference in private and public test scores reflects omitted variables such as family background (Muralidharan et al. 2015). Despite the large quantity of education-related research in India, the literature on training-focused government partnerships with NGOs such as Pratham remains limited. This paper contributes by performing a causal analysis of these partnerships.

The remainder of the paper proceeds as follows. Section II provides background and an overview of methodology, section III discusses the data, section IV outlines the difference-in-differences design, section V presents the results, and section VI concludes.

II. Background and methodology

Through classroom observation and analysis of the Annual Status of Education Report (ASER) data, researchers have identified key problems to address through Pratham's government partnerships. The first relates to teacher training. The Right to Education law in 2010 stipulates that all applicants for teaching positions are required to pass a teacher eligibility test to qualify to teach. However, the training that follows is inconsistent. Traditionally, teacher training takes place through classroom lectures on theoretical concepts, but little ensures that these lessons translate to classroom performance (Banerji, 2015). The impact of ineffective training fuels the second concern: the speed of government school curricula. In 2015, Lant Pritchett detailed a mismatch between children's learning levels and classroom curricula, causing teachers to teach concepts too advanced for their students to grasp. Since 2004, Pratham has led programs such as "Read India" to address these concerns.

In 2016, the NGO implemented a series of government partnerships that provide teacher trainings and initiate programs that group children by learning level, hoping to encourage students who are behind to catch up to their peers. Schools participating in the partnerships receive on-site mentoring and monitoring from government officials, with implementation support from Pratham teams. The officials—previously trained by Pratham—instruct teachers to group children according to simple, one-on-one math and reading assessments. These groups then participate in activities focused on their learning level. As the children make progress, teachers move them from group to group. Throughout this process, the government leaders guide discussions, give feedback, observe classroom sessions, demonstrate activities, and co-create strategies with teachers. All of these activities result from the Pratham-government partnerships and form the basis of my analysis.

Pratham implements government partnerships at three levels: state-wide (involving all public school districts within a state), state-level (involving select districts within a state), and district-level (involving only specific districts). The number of children reached by each partnership varies from state to state and has increased over time. For example, in Uttar Pradesh, about 213,000 children were affected in 2016, which increased to approximately 8.7 million children by 2018. To date, 14 states have participated in Pratham government partnership programs, and 29 states remain unaffected, with the exception of potential spillover effects. Thus, we can exploit differences across states with and without Pratham involvement at the government level to estimate the causal impact of the partnerships on student achievement.

Anecdotal reports of the impact of level-appropriate teaching cite immediate effects, suggesting that children's learning levels should change during the year of program implementation. To determine whether or not these effects exist empirically, I will use a difference-in-differences identification strategy. Rather than analyzing the impact in all 14 states, I will focus on Uttar Pradesh because it compares well to Rajasthan, a state that does not have a Pratham-government partnership. I confirm the results of this analysis by creating synthetic controls for other states representative of different levels of implementation that have significant numbers of affected students: Jharkhand, Himachal Pradesh, and Madya Pradesh.

III. Data

All data for this analysis come from the Annual Status of Education Report (ASER), a survey that measures literacy and numeracy skills of children ages 3-16 in rural areas of every Indian state. To focus their efforts more effectively, Pratham initiated ASER in 2005. The survey mobilized hundreds of thousands of young adults to collect data in a census, door-to-door format. The volunteers conduct these "citizen-led basic learning assessments" using surveys that not only ask about family background and school enrollment, but also require children to complete three standardized assessments: a one-page mathematics test, a one-page reading exercise in Hindu, and a one-page reading exercise in English. These assessments rank students on standardized scales. For example, children are presented with a sheet of paper with four levels of math problems and are asked to solve each. The first level tests number recognition (1-9) and the last level tests three digit by one-digit division. After asking the child to complete the worksheet, volunteers rank her on a scale of 1-5 based on the highest-level problem that she solved successfully. The surveyors go village by village, dividing each village into four geographic sections or randomly selecting four hamlets. Within each section or hamlet, they start in the center of the area and survey every 5th house, using a geographically randomized evaluation method. Volunteers survey approximately 20 houses in every village and select villages from approximately 570 rural districts. An autonomous ASER Centre now collects and processes all ASER data each year, but the standardized examinations remain comparable over time.

While all survey-based data encounters measurement error, the ASER method provides several advantages over traditional, school-based assessments. By randomly selecting households and surveying all children ages 3-16, the system includes an accurate evaluation of children that government-led assessments may omit because they are not enrolled in traditional government schools. In particular, the household method relates to enrollment rates in private versus government schools. Geeta Kingdon (2007) reveals that the size of the private education sector is underestimated in official data, while ASER captures a more realistic perspective. Her opinion hinges on two advantages of ASER data: (1) self-reported data avoids corruption from government school officials looking to increase enrollment statistics and (2) ASER data is not limited to official school censuses, which are held only in government-recognized schools (2007). Finally, ASER data presents high agreement in repeated test administrations. For a group of 540 children assessed by the same team of examiners on two testing occasions, the test-retest correlation coefficients for the ASER-reading test is .95 and the ASER math test .90 (Vagh, 2010).

ASER data aggregates approximately 540,000 observations of children ages 3-16 to calculate the percent of students reaching grade-level performance in each state. It also breaks estimates down by private and government schools after surveying parents on their children's enrollment. In this paper, I use ASER data on Standard III math scores. I focus on Standard III because the partnership in Uttar Pradesh, which affects students Standards I-V, should impact students in Standard III throughout the post-treatment period (2016-2018). The most commonly used metric for Standard III math performance in India is the percent of students who can perform a simple subtraction problem. Summary statistics for Uttar Pradesh and Rajasthan, the two states of interest for the difference-in-differences estimation, appear in Table 1.

Table 1: Descriptive Statistics for Students in Uttar Pradesh and Rajasthan Before and After 2016

	Means with standard deviations in parentheses			
	Uttar Pradesh		Rajasthan	
	Pre	Post	Pre	Post
% Std III that subtracts	22.81	24.90	25.00	19.20
	(2.08)	(1.70)	(4.00)	(1.80)
% Government Std III that subtracts	13.51	9.55	14.95	9.55
	(6.01)	(1.65)	(6.04)	(1.45)
% Enrolled in private school	41.84	50.90	35.13	37.50
	(7.47)	(1.20)	(5.07)	(1.70)

Notes: This table presents means calculated based on all pre- and all post-treatment data.

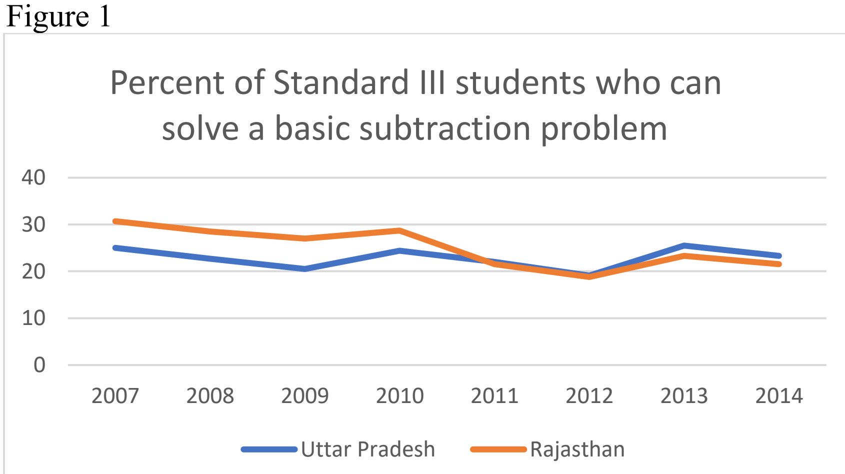
IV. Uttar Pradesh vs. Rajasthan

Parallel Trends Assumption

The program in Uttar Pradesh lends itself to causal analysis because student scores in Rajasthan, a neighboring state, provide a counterfactual outcome for scores in Uttar Pradesh. As two of the largest states in India, Uttar Pradesh and Rajasthan have similar geographic characteristics, markets, and religious compositions. Along with their demographic similarities, the states produce similar student outcomes among primary and secondary schools. Because of these commonalities, I assume that test scores in Rajasthan serve as a valid counterfactual for test scores in Uttar Pradesh.

To test this assumption, I examine whether the trends in Standard III math scores among students in Rajasthan and Uttar Pradesh were parallel prior between 2007 and 2014. I graph state-level student subtraction rates for both states prior to the Pratham Partnership in Figure 1.

Figure 1



Notes: This figure graphs the pre-treatment trends in Rajasthan and Uttar Pradesh, measuring the percent of students who can subtract over time.

Figure 1 exhibits the similarities between student performance in Uttar Pradesh and Rajasthan. However, to assess the common trends assumption more directly, I perform a regression to ensure that there is not a significant difference in trends using only pre-treatment data. To run this test, I use the following model:

$$StandardIIIMath = \beta_0 + \beta_1 year + \beta_2 treated + \beta_3 year * treated + e \qquad (1)$$

where β_3 measures the effect that the year has on test scores in Uttar Pradesh (the treated state) relative to Rajasthan (the untreated state) before the program was initiated. The results of this model reveal no significant difference in trends over time in Uttar Pradesh and Rajasthan (see Table 2).

Table 2: Estimated effect of year on pretreatment data

Variable	Coefficient	Standard Error	t	P>t	95% Confidence Interval	
Year*Treated	3.066369	2.384323	1.29	0.201	-1.66406	7.796798

Notes: This table shows the coefficient for the interaction term indicating the difference in time trends in Uttar Pradesh in all pre-treatment years. The results are not statistically significant.

Since there is no significant effect on scores for students in Uttar Pradesh in any given year prior to treatment, I proceed with the assumption that trends in Uttar Pradesh were not significantly different than those in Rajasthan before the partnership began.

Difference-in-Differences Methodology

To identify the causal effect of the Pratham Partnerships, I employ a difference-in-differences model that measures the change in the percent of Standard III students who can subtract in Uttar Pradesh relative to the change in Rajasthan after the program was implemented. Because Pratham began partnering with Uttar Pradesh in 2016 and because trends were parallel prior to 2016, we can attribute changes after 2016 to the Pratham partnership. The baseline is given as:

$$StandardIIIMath = \beta_0 + \beta_1 post + \beta_2 treated + \beta_3 post * treated + e \qquad (2)$$

where StandardIIIMath is the percentage of students who can subtract; post is an indicator for the period after implementation in 2016; treated is an indicator for the existence of a Pratham Partnership; and β_0 is the y-intercept and e is an error term. The interaction effect, β_3, measures the change in scores in Uttar Pradesh after the partnership began relative to the change in Rajasthan. Because years of data are limited, I use OLS standard errors, acknowledging that there is some potential for autocorrelation in the error terms over time.

V. Results

The regression results in Table 3 reveal the effect of the program on test scores in Uttar Pradesh in years 2016 and 2018 relative to Rajasthan.[1] The difference-in-differences coefficient reveals a 7.9 percentage point statistically significant advantage in test scores in Uttar Pradesh, implying a divergence in trends between Uttar Pradesh and Rajasthan in the post-treatment period. This suggests that the Pratham partnership, implemented in 2016, led to a short-term improvement in student performance at the state level. Figure 2 illustrates the change in trends in the years following implementation.

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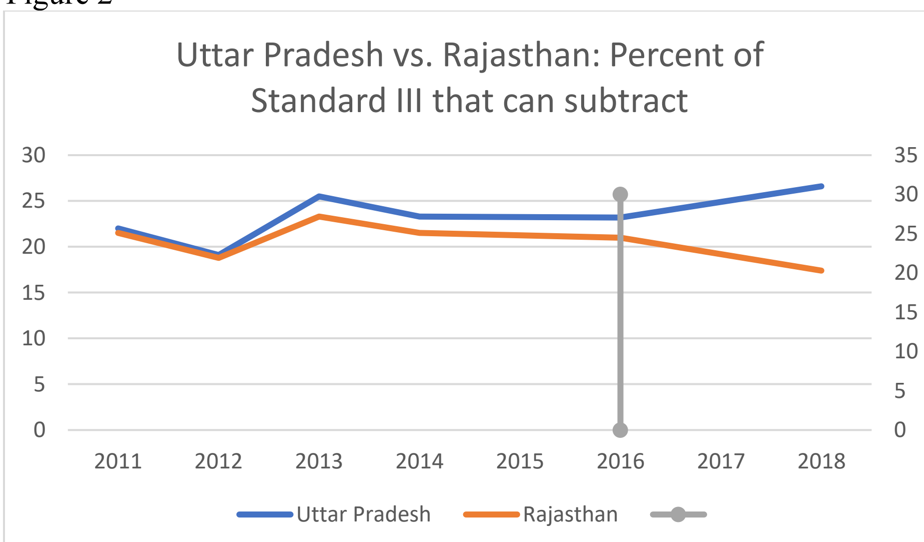
[1] Data from 2017 is not included because in 2017, the ASER Centre conducted a special report surveying children ages 14-18 instead of the standard assessment of children ages 3-16.

Table 3: Estimated effect of treatment in post-implementation period

Variable	Coefficient	t	P>t	95% Confidence Interval	
Diff-in-diffs	**7.8875***	2.13	0.049	0.05	15.73
	3.70				
Time	-5.80	-2.22	0.041	-11.34	-0.26
	2.62				
Treated	-2.19	-1.32	0.205	-5.69	1.32
	1.65				

Notes: This table displays regression coefficients for the difference-in-differences regression using state-wide ASER estimates. The * indicates that the coefficient in column 1 is significant at the 5% level.

Figure 2



Notes: This figure adds years 2016 and 2018 (post-implementation) to Figure 1.

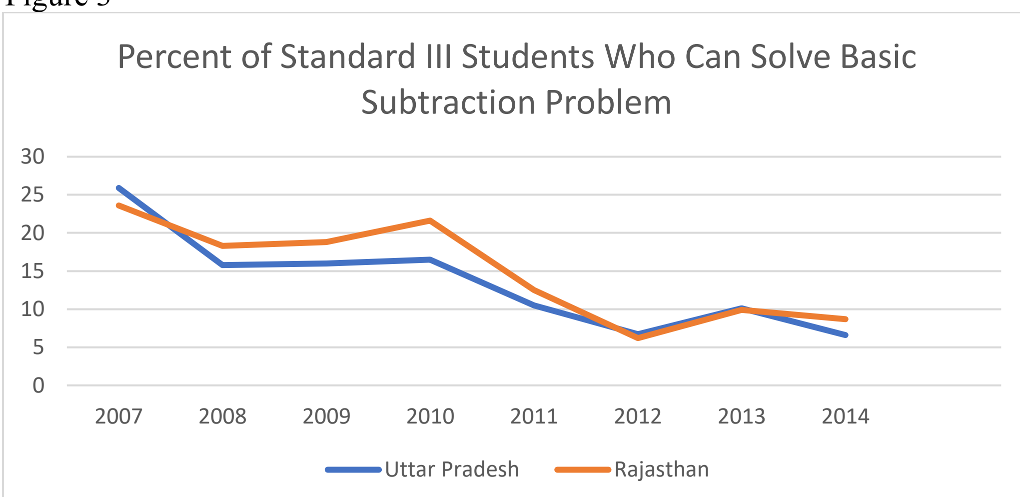
VI. Robustness

To further determine whether the change in Uttar Pradesh's math scores occurred as a result of the Pratham Partnerships, I perform the same regression but restrict data to children who attended government schools, excluding private school students. While this data is more prone to measurement error because it requires a second piece of survey information, it is a more relevant measure of the program's impact because Pratham-government partnerships only directly affect government schools.

Parallel Trends Prior to Treatment

I use Equation 1 again to examine parallel trends among government schoolchildren. In this regression, however, the data consists of the percent of government-school students in Standard III who can subtract instead of the statewide percent of students in Standard III who can subtract. Regression results show no significant difference in trends between Uttar Pradesh and Rajasthan (see Table 1 in the Appendix). Figure 3 provides a visual representation of the trends.

Figure 3



Notes: This figure illustrates pre-treatment trends in Uttar Pradesh and Rajasthan for students who attended government schools.

Difference-in-Differences

When examining the causal impact of program implementation in Uttar Pradesh, I use the same difference-in-differences regression as above, again restricting the state-level data to government-school students only. However, contrary to the effects shown using state-wide data, the results of the government school regression show no significant difference between scores in Rajasthan and scores in Uttar Pradesh after program implementation (see Table 3).

Table 4: Estimated effect of treatment in post-implementation period among government schoolchildren

Variable	Coefficient	t	P>t	95% Confidence Interval	
Diff-in-diffs	1.44	0.21	0.84	-12.96	15.84
	6.79				
Time	-5.40	-1.12	0.28	-15.58	4.78
	4.80				
Treated	-1.44	-0.47	0.64	-7.88	5.00
	3.04				

Notes: This table displays all coefficients for the difference-in-differences regression using government student data only. No results are significant.

The insignificant results of the difference-in-differences coefficient in Table 3 suggest that the presence of Pratham-government partnerships in Uttar Pradesh had no impact on Standard III math scores among government schoolchildren. This finding calls the results from the initial regression into question—theoretically, government schoolchildren should show larger effects than the overall population. I consider various potential explanations for this finding in Section IX.

Synthetic Controls

To further investigate the null effect on government schools, I examine the impact of the partnerships on government students in other affected states. Comparing the results in Uttar Pradesh to the effect of Pratham partnerships in other states is difficult because these states lack counterfactual trends. Nevertheless, synthetic control specifications allow me to estimate the impact of the partnerships in Jakharand, Madya Pradesh, and Himachal.

The synthetic control method, developed by Abadie et al (2010), creates a weighted average of potential control states, matching pre-treatment outcomes for the treated state to minimize the average of the squared discrepancies between test scores in the treated state and its synthetic counterpart (MSPE) for all specific pre-treatment periods. It restricts all weights to be nonnegative and sum to one, creating a synthetic control state that best replicates trends in the treated state prior to implementation of the Pratham intervention in 2016. Thus, my identification strategy rests on the assumption that the synthetic control state represents a valid counterfactual trend for test scores after Pratham-government partnership was initiated.

I use this method to create synthetic controls for Jakharand, Madya Pradesh, and Himachal. Donor pool states include a set of 9 states unaffected by the Pratham-government partnerships, with ASER test score data starting in 2007. With these states, I match on pre-treatment trends in test scores for government schoolchildren to create synthetic controls. I also run placebo tests for each synthetic control to examine whether the difference between the treated and synthetic units is uniquely large for the state of interest. The synthetic control for Jakharand and the accompanying placebo test appear in Figures 4 and 5 below. The rest are in the Appendix along with unit weights. None show a statistically significant effect of the Pratham partnership, confirming the null results found among government students in Uttar Pradesh.

Figure 4

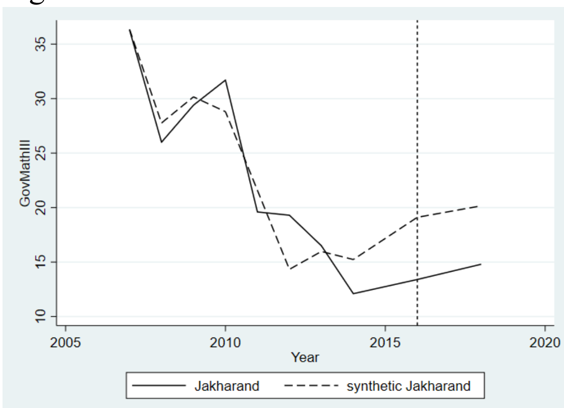


Figure 5

Notes: Figure 4 shows the trends over time for Jakharand and synthetic Jakharand, revealing no divergence in the post-treatment period. Figure 5 puts the gap between synthetic and real Jakharand in the context of statistical inference, revealing no significant difference between the them compared to placebos for other states.

VII. Discussion and Conclusion

The results found using government-school data raise a new question: Why does the effect of Pratham-government partnerships disappear when focusing on government schools, and is the change in scores seen at the state-level attributable to the Pratham programs? To address these concerns, I examine four potential explanations: measurement error, spillover effects, changes in private schools, and short run versus long run effects.

1) Measurement error

As explained in Section III, volunteers collect all ASER data in a census format. Thus, adding variables such as government-school enrollment increases chances of including misreported or incorrectly input data. Furthermore, some families give incomplete information, not disclosing whether or not children attend a government school. This non-disclosure may limit the amount of usable sample data. Either form of measurement error could bias the results in the government-only regression, suggesting that the effects in the government school regression are less representative than those at the state level.

2) Spillover effects

Because the divergence between scores in Rajasthan and scores in Uttar Pradesh disappears

when private school students are removed from the data, it is likely that the divergence was driven by improvements among private school students. Before considering an improvement in private schools themselves, I consider potential spillover effects from the Pratham programs.

While spillover is unlikely during a short period of time from public to unaided schools, government-aided private schools may absorb Pratham methods.

Many private schools in India are referred to as "aided schools." They receive substantial funding from the government, and although they are nominally run by management boards, they are governed by the state (Kingdon 2017). As a result, they adopt teaching practices similar to those in government schools and are often excluded from discussions of "private schooling." Thus, because of their close connection with traditional government schools, aided-schools are more likely to be indirectly influenced by Pratham-government partnerships than unaided private schools.

Nevertheless, ASER data does not discriminate between aided private and unaided private schools. According to Kingdon (2017), it combines the two into a single category 'private'. This categorization implies that if the effects of the Pratham partnerships spill into government-aided schools, by removing the private school category from our analysis, we remove a group of students who may benefit from the treatment. Kingdon presents estimates of children in rural areas who attend private, unaided schools. Her estimates rely on different methodology than ASER estimates, but theoretically should produce similar results. In Uttar Pradesh, her estimate of the percent of students enrolled in private schools is almost 10 percentage points lower than the ASER estimate. In Rajasthan, the estimate is approximately 5 percentage points lower (2017). Attributing this difference to the children in aided private schools—included only in the ASER data—suggests that the ASER estimates for test scores in Uttar Pradesh include a larger percentage of children attending aided private schools. In the context of my analysis, this provides some evidence for the theory that the divergence in test scores between Uttar Pradesh and Rajasthan was spurred by the students in government-aided schools who have potential to absorb effects of the Pratham intervention. In other words, the results seen in the original regression (Equation 2) may come from the influence of Pratham-government partnerships on students in aided private schools.

3) Changes in private schools

Another potential explanation is that the effects are driven by children not only in aided private schools, but also in unaided private schools. In both Kingdon and ASER estimates, the percentage of students attending private school in Uttar Pradesh is slightly higher than the percentage in Rajasthan. This difference could explain divergence after 2016 when private schools are included.

Channels through which private schools could create a gap in scores between Uttar Pradesh and Rajasthan vary. There were no significant policy changes in either state regarding private schools in 2016. However, there has been rapid growth in private schools across India over the last 10 years. This growth influences the variety of quality of private schools available in each state—Uttar Pradesh's higher rates of private school enrollment may be leading to improved scores over time.

To asses this hypothesis, I run the difference-in-differences regression in Equation 2 for government schools, controlling for the percent of students ages 6-14 enrolled in private school in each state. This regression relies on the assumption that students did not enroll in private school because of the Pratham partnerships—if there were some direct relationship between the partnerships and private school enrollment, findings would be insignificant. The results of this regression are in Table 2 of the Appendix. Initially, controlling for private school enrollment reveals a positive effect of treatment on government school test scores in Uttar Pradesh after 2016. This result matches the result found in the initial regression using data for all students. However, the addition of private school enrollment weakens the parallel trends assumption, suggesting that the commonalities in test scores prior to treatment may be affected by private school enrollment. This finding implies that there may be a small statistically significant difference between test scores in Rajasthan and Uttar Pradesh even before 2016, which must be acknowledged when accepting the results of either difference-in-differences regression. Regardless, the results of the private-school enrollment regression indicate that the null difference in outcomes found in the government-school-only regression may be clouded by the percent of private school students in each state.

4) Short run versus long run effects

Finally, both the state-level and government-school only regressions work with a limited amount of post-treatment data. Because the programs were implemented beginning in 2016, effects using both versions of the data reveal only the immediate impact of the intervention. Thus, while the results may conclude that the Pratham-government partnerships have a questionable level of impact on student test scores in the short run, there is potential for impact to increase in the future. The partnerships depend on teacher-training, which implies that over time, Pratham methods will become more ingrained in teaching practices. Moreover, teachers and students will adapt to the group-based learning style, increasing effectiveness. The initial regression may indicate future improvement in Uttar Pradesh scores, but more post data is necessary to analyze the longer-term impact.

Conclusion

Overall, the findings show no clear, short-run impact of the Pratham-government partnerships on the academic achievement of government school students. Despite the lack of clarity among government schools, the state-wide ASER regression—with the largest sample and most reliable data—suggests that Pratham partnerships may be influencing students indirectly, successfully impacting student outcomes. Adding data from future years to the difference-in-differences model outlined in this paper may reveal the long-run effects of the program. Future research is also needed to account for the effect of private school enrollment—both aided and unaided—on changes in aggregate student outcomes. Such research, combined with existing data on the before and after effects of Pratham-government partnerships at the student level, will depict the true effectiveness of the partnerships, allowing the organization to ensure that "Every child is in school and learning well."

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Appendix

Table 1: Estimated effect of year on pretreatment data

Variable	Coefficient	Standard Error	t	P>t	95% Confidence Interval	
Year*Treated	1.435119	2.129679	0.67	0.502	-2.7901	5.660341

Table 2: Estimated effect of treatment in post-implementation period, controlling for private school enrollment

Variable	Coefficient	t	P>t	95% Confidence Interval	
Diff-in-diffs	7.21*	2.46	0.03	0.96	13.47
	(2.93)				
Time	-3.35	-1.65	0.12	-7.69	0.99
	(2.03)				
Treated	4.36**	3.02	0.01	1.29	7.43
	(1.44)				
%Private	-0.86***	-8.68	0.00	-1.08	-0.65
	(0.10)				

Table 3: Unit weights for Jakharand synthetic control

State	Weight
Assam	0.462
Gujarat	0.229
Haryana	0.056
Madya Pradesh	0
Mahashtra	0.034
Manipur	0
Odisha	0.072
Rajasthan	0.146
Tamil Nadu	0

Table 4: Unit weights for Himachal synthetic control

State	Weight
Assam	0
Gujarat	0
Haryana	0
Jakharand	0
Madya Pradesh	0
Mahashtra	0.448
Manipur	0.552
Odisha	0
Rajasthan	0
Tamil Nadu	0
Uttar Pradesh	0

Figure 1

Madya Pradesh (no apparent effect—this is actually a difference-in-differences Mahastra)

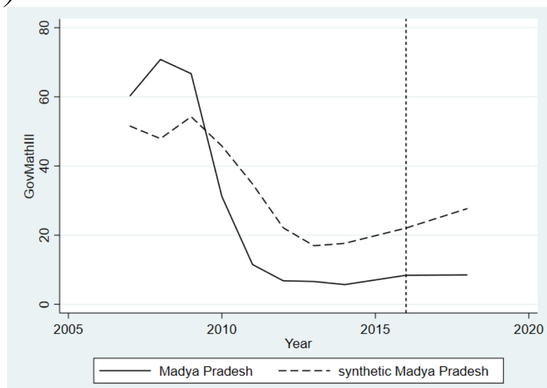

Figure 2

Himachal Synthetic Control (decrease—no apparent positive effect)

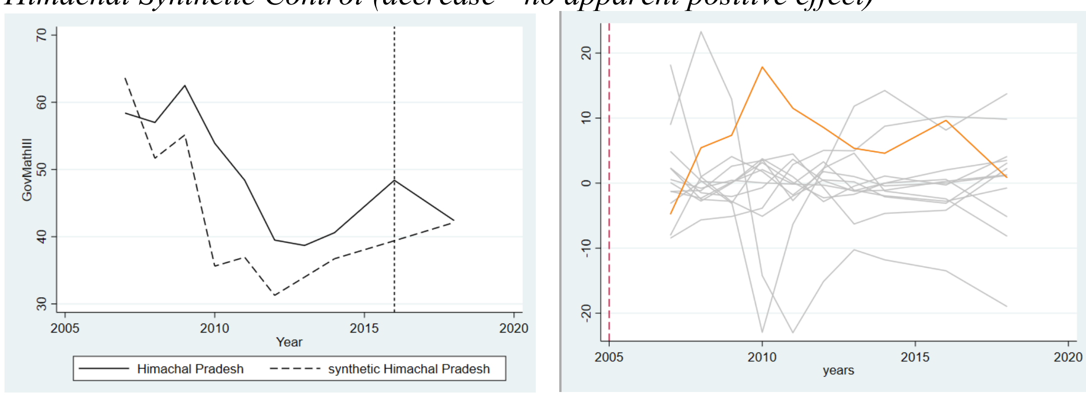

Figure 3

Uttar Pradesh Synthetic Control