School Disruptions: The Effects of Conflict on Student Academic Achievements in Kashmir

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Abstract

This paper examines the effects of conflict-induced school closures on student achievement. We exploit a sudden spike in violence in 2010 that led to school closures in Kashmir but did not affect adjoining Jammu and Ladakh regions. Using difference-in-differences, we estimate that students exposed to violent conflict scored 0.13 and 0.22 standard deviations lower in reading and math tests after the unrest. Heterogeneity analyses reveal that girls and weaker students are the most adversely affected. The results are robust to various specifications, test score measurements and selection into violence.

JEL Classification: I21, O12, I25, O15, I24, D74

Keywords: Conflict, Education, Human Capital, Kashmir, DID

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1 Introduction

Violent conflicts, often referred to as *"development in reverse"* (Collier et al., 2003), are a common phenomenon in developing countries (Brown & Velásquez, 2017). In recent decades, localized civil armed conflicts and drug-related violence have taken precedence over state wars (Singh & Shemyakina, 2016), and the average duration and frequency of these conflicts has been increasing significantly over the last five decades (Blattman & Annan, 2010). Although the detrimental impacts of civil conflicts may extend well beyond the casualties of those directly involved, very little is known about the other indirect effects of conflict on the population of impacted regions. These conflicts, in particular, significantly impact the formation of human capital and the accumulation of education. The recent empirical evidence on the microeconomic impacts of violent conflict indicates that the conflict reduces education accumulation[1], but only a few studies show how conflicts affect the quality of education.

This paper investigates the effects of civil conflict in Kashmir by examining how exposure to civil unrest during the school age affected educational quality as measured by student performance in basic literacy and numeracy tests on a national standardized exam. Understanding the consequences of conflict on reading and arithmetic competency is particularly important from the perspective of developing countries, as ongoing and protracted conflicts would exacerbate the problem of diminished educational quality further[2] and undermine their potential to accomplish "Quality Education", which is the Sustainable Development Goal 4. Although the Kashmir conflict began as an armed conflict in 1989, since 2008 it has primarily taken the form of a civil conflict (CDR, 2010). The summer of 2010 witnessed an unprecedented violent conflict in Kashmir in which at least 112 civilians were killed across all the districts of Kashmir and at one location in the Poonch district of the Jammu region (CDR, 2010), causing sudden spike in the working days lost to the conflict in recent history of the state. The deaths of civilians created safety concerns and put lives in danger throughout the Kashmir valley, where the conflict is generally seen as opposed to the other two regions of the state with no

[1] For example, Akresh & de Walque (2008) find that kids exposed to the Rwandan genocide have an 18.3 percent drop in average years of schooling. Shemyakina (2011) discovers that people of school age during the Tajik civil war are much less likely to finish their compulsory schooling. León (2012) shows that the average Peruvian exposed to civil strife has 0.31 fewer years of schooling as an adult. According to Islam et al. (2016), interruption in primary education caused by war exposure in Cambodia reduces completed years of schooling by 2.9 - 3.9 months for males and 2.2 – 3.5 months for women.

[2] According to the UNESCO (2017), six out of ten students globally could not demonstrate minimum proficiency in reading and maths. This disparity in schooling and education is significantly more pronounced in less developed countries (LDCs).

conflict. In this context, we should expect indirect impacts of violence on student test scores, in addition to direct damage, because violence may disrupt school calendars, raise absenteeism among instructors and students, and cause significant psychological suffering among kids (Monteiro & Rocha, 2017).

Estimating the causal effects of violent conflicts on educational outcomes can be difficult since conflict-affected areas may be considerably different from unaffected regions, which confounds the cross-sectional investigation that seeks to identify the impact of violence (Monteiro & Rocha, 2017). We overcome this challenge by isolating the impacts of violence from other types of socioeconomic disadvantages that correlate with educational performance using a plausibly exogenous temporal and geographic variation in exposure to civil conflicts. In our case, the conflict is predominantly concentrated in one region of the state of Jammu and Kashmir, while the other regions are immune to violent conflict. The recent shift from insurgency-related violence to civil conflict has caused the violence to concentrate in one region of an otherwise identical state and the 2010 unrest, in particular, impacted only the inhabitants of Kashmir valley districts (CDR, 2010), whereas the rest of the state saw no violence, which allows us to quantify the causal effects using the difference-in-differences (DID) approach.

We provide evidence that the students exposed to the 2010 unrest in the Kashmir valley perform worse on standardized reading and math tests. Conflict exposure reduces the reading test scores by 0.13 standard deviations and the math test scores by 0.22 standard deviations. These treatment effects are quite significant compared to a few closely related studies that examine the impact of conflicts on test score outcomes, most of which study the impact of highly localized drug-related violence. For example, drug-related violence caused math scores to diminish by 0.054 standard deviations but had no effect on reading performance in Brazil (Monteiro & Rocha, 2017) while in Mexico it was associated with a 0.1 standard deviation drop in exam scores (Michaelsen & Salardi, 2020). Further, civil conflict caused a deterioration of 0.15 and 0.08 standard deviation in Colombia (Gómez Soler, 2016) and 0.03 and 0.02 standard deviations in West Bank (Brück et al., 2019) on math and language exams respectively. Other related studies discover effect sizes that are also smaller in magnitude. Since the academic year in Kashmir typically extends from March to November, given the fact that the ASER surveyors could not visit the state of J&K to conduct the survey in 2010 due to security tensions and that the surveys are generally conducted around October each year (Chakraborty & Jayaraman, 2019), our results further indicate that the effects of violence persist over time as we find these detrimental effects two years post the unrest and at least one year after the exposure. Given that there was no unrest in 2011 and the schools operated as usual, and children were engaged in learning throughout the 2011 academic year; if school instruction benefits these students in any way, then the engagement in learning at school must compensate for some of the negative impacts of conflict exposure. Therefore, one may reasonably interpret our estimates as the lower bound of the negative effect of conflict on educational quality.

Our results further reveal that the impact of conflict can cause a severe loss in the ability of higher grade (6-12) students to read the basic grade one and two texts and solve fundamental numerical problems at the level of grades three and four. However, we do not find any statistically significant and economically meaningful effect on the students who lie in the upper tail (above the median) of the test scores distribution. This is a significant finding in the literature examining the microeconomic effects of violent conflicts. While the existing literature shows that the effect of conflict on test score outcomes is transitory (Monteiro & Rocha, 2017; Michaelsen & Salardi, 2020; Brück et al., 2019)[3] and has no effects on the students in the far right tail of the distribution (Brück et al., 2019)[4], our results indicate that effects persist two years post the unrest and are significant for the students in the lower tail of the test score distributions. These findings together suggest that conflict can affect students directly via a reduction in test score outcomes and indirectly by widening the learning gaps between the high and the low-performing students, which can have long-term consequences for income inequalities (Rodríguez-Pose & Tselios, 2009).

This paper contributes to the literature on the microeconomic effects of violent conflict on education[5]. The existing studies in the literature show that armed or civil conflicts or

[3]Monteiro & Rocha (2017) finds that drug-related violence in Brazil significantly affects test scores in the short term, but its effects are transient. The impacts, in particular, disappear within the first trimester of the academic year that follows the academic year in which violence occurs. Michaelsen & Salardi (2020) discovers that drug-related violence in Mexico has a negative impact on educational achievement both in the short term (7 days) and in the long run (9 months). The short-term consequences of violence are far more severe than the long-term consequences. Violence during a week before the tests (at least three homicides) is associated with a 0.1 standard deviation drop in exam scores. The long-term effect of violence is the same, but the level of violence is as high as 100 homicides or more. Brück et al. (2019) also discover that the negative effect is greatest and most significant for conflict events that occur just one month before the exams.

[4]Brück et al. (2019) find that the violence in Palestine negatively impacts the total test scores up to the 90^{th} percentile of the conditional test score distribution.

[5]See for example Brück et al. (2019); Justino (2011); Monteiro & Rocha (2017); Shemyakina (2011); Weldeegzie (2017); Bertoni et al. (2019) among others. For review see Blattman & Miguel (2010) and Verwimp et al. (2019)

drug-related violence significantly and negatively impact educational attainment[6]. However, there is very sparse evidence relating to the impact of conflict on the quality of education, particularly on how conflicts impact the foundational skills to read and solve simple math problems. The limited number of studies which examine the impact of violence on educational quality find that conflict negatively affected the chances of passing the final exam, the total test score, and the probability of getting admitted to the university for Palestinian high school students in the West Bank (Brück et al., 2019), reduced performance on exit exams in Colombia (Gómez Soler, 2016) and test scores in Turkey (Kibris, 2015), Brazil (Monteiro & Rocha, 2017) and Mexico (Michaelsen & Salardi, 2020).

We contribute to this scant but growing literature in the following significant ways: First, we contribute by providing, what is to the best of our knowledge, the first causal estimate of the impact of unrest on the quality of education at the granular level using student test scores on national standardized tests. This is, to the best of our knowledge, the first attempt to investigate the relationship between civil unrest and literacy and numeracy competence of children in grades 1-12 in a developing country. Therefore, our findings are crucial in determining the extent to which civil conflicts impact the ability of exposed cohorts to read basic grade two level text and solve simple arithmetic problems at grade three and four levels. Second, we are able to determine whether exposure to conflict is indeed transitory in nature. Unlike previous studies which find adverse impacts of violence fading within one to three months of the exposure (Monteiro & Rocha, 2017; Michaelsen & Salardi, 2020; Brück et al., 2019), we document that the effects do not fade away at least two years post the conflict exposure. Previous research has shown that educational interventions only have a short-term impact on test score outcomes and then quickly disappears (See Andrabi et al. (2011)). So, if the effects of conflicts last for a long time, they can cause a huge drop in the quality of education, which is already abysmal in conflict-ridden developing countries. Third, we present novel evidence of conflict's heterogeneous impact at the individual level. We show that the conflict has a negative and statistically significant impact on higher grade (6-12) students' ability to read and solve simple math problems at the difficulty levels of grades three and four but has no impact on the students in the upper tail of test scores distribution. This demonstrates that conflict have disproportionately greater impacts on the low-performing students primarily and generates educational inequalities, which may lead to income inequalities among those exposed in the long run.

[6] See Akresh & de Walque (2008); Akbulut-Yuksel (2014); Justino (2011); Shemyakina (2011); León (2012); Weldeegzie (2017); Brown & Velásquez (2017) among others.

The rest of this paper is organized as follows: Section II presents a brief background on the conflict and educational disruption in Kashmir. Section III describes the data, and in Section IV, we discuss the methodology with the identification strategy used to identify the treatment effects. We present the results of the study in Section V, following which we carry out certain robustness checks in Section VI. We close the paper in Section VII with a discussion of the results and the concluding remarks.

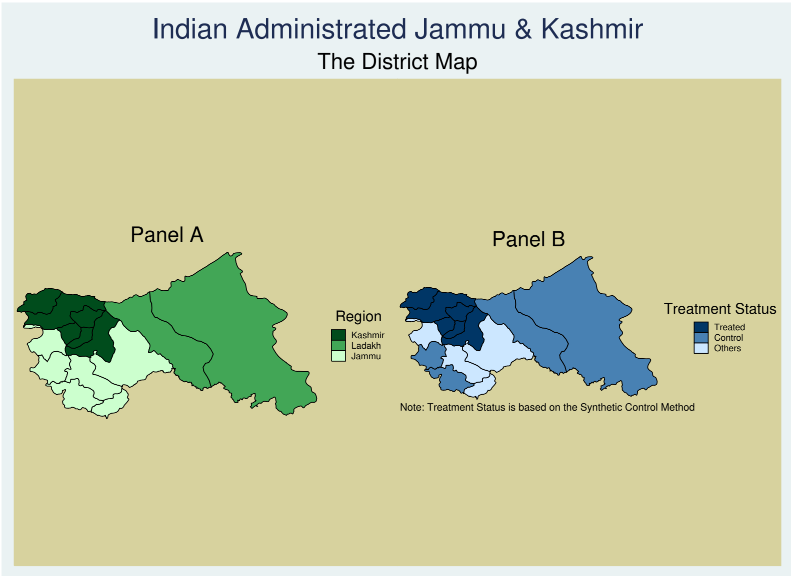
2 Kashmir Conflict and Education Disruption: A Brief Background

Jammu and Kashmir (J&K) is the northernmost state[7] of India, which shares international borders with Pakistan and China and is divided into three parts: Jammu, Kashmir, commonly known as the Valley, and Ladakh (See Figure 1). The dispute between India and Pakistan over J&K state has resulted in three wars in 1947, 1965, and 1999. The Kashmir conflict erupted in 1989 as an armed battle and escalated the following decade, but unlike in the 1990s and early 2000s, when bombings, grenade explosions, and cross-firing were the norm, the conflict has recently primarily taken the form of a civil conflict (Parvaiz, 2017) where *"the stone has replaced the gun"* (CDR, 2010), and teenagers and pre-teens have also become more involved in and participated in stone-pelting and strike enforcement (Shah, 2019). According to the official data, over 6,000 law and order events were reported between January 2010 and May 2017, compared to around 2,000 insurgency-related occurrences (Parvaiz, 2017), while approximately 13,000 stone-pelting incidents were reported in Kashmir between 2009 and 2019, with nearly 5,600 occurring during the 2010 and 2016 mass uprisings alone (Ganie, 2021). We present the year-wise data on law & order cases and stone-pelting incidents in Appendix Figure A.1.

In the recent history, the year 2010 saw an unprecedented summer unrest in which at least 112 civilians were killed after security forces opened fire on protests by civilians in several locations throughout the Kashmir valley and at one place in the Poonch district of Jammu province (CDR, 2010). The researchers at the Centre for Dialogue and Reconciliation (CDR), New Delhi, interviewed 97 of these 112 families to learn more about the socioeconomic circumstances and lives of the young people slain in the summer unrest

[7] On August 5, 2019 the state of Jammu & Kashmir was bifurcated into the two separate Union Territories, UT of J&K and the UT of Ladakh. However, this division happened after the study period of the current paper. For more details, see https://en.wikipedia.org/wiki/The_Jammu_and_Kashmir_Reorganisation_Act,_2019

Figure 1: *Map of Jammu & Kashmir*



Note: The Map is created using country level data from DIVA-GIS. For details, see https://diva-gis.org/gdata

of 2010 in Kashmir and the events that led up to their deaths. They find that these 97 slain people belonged to each district of the Kashmir valley. According to the report, the Baramulla district suffered the most casualties, accounting for 39 of the 97 fatalities. Of the remaining 58, 16 were from Srinagar, 12 were from Anantnag, 11 were from Pulwama, 7 were from Budgam, and 3 were each from Shopian and Kulgam. Each of Ganderbal, Kupwara, and Bandipore witnessed two killings. The unrest was widespread throughout the Valley; however, it was more intense in some regions, as is evident from the number of incidents.

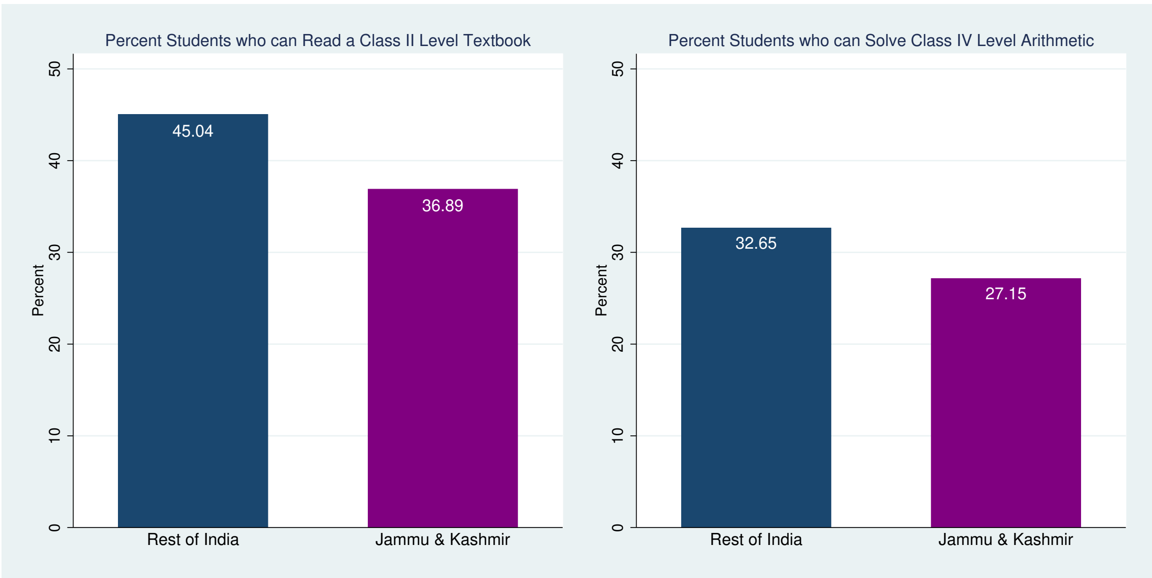
In the Kashmir Valley, the school academic year extends from March to October, when exams for the current academic year are conducted, and the schools usually close for a winter break of nearly 3 months in November and for 2-3 weeks for summer vacations, usually in June or July. The education sector in Kashmir is periodically disrupted by the violence and curfews, shutdowns (*hartals*), and other such law and order situations when schools remain closed for several months due to continuous shutdowns in major agitations. The mass uprising of 2010 started in May and lasted till the end of September, which resulted in continuous curfews and shutdowns in Kashmir districts, leading to school and college closures (Ministry of Home Affairs, 2010) for about four months[8]. The Appendix Figure A.2 shows the number of working days lost to the Kashmir conflict due

[8] https://www.indiatoday.in/india/story/schools-reopen-in-kashmir-valley-after-4-months-82724-2010-09-27

to strike calls, curfews, and protest demonstrations. In 2010, 112 working days were lost to the mass unrest comprising most of the academic year, and this was the worst year in terms of working days lost to conflict in Kashmir in the recent past. We examine the impact of the 2010 mass unrest because only a meagre number of days were lost before and after 2010, and our data only allows us to analyze the effects of this mass unrest.

These school interruptions and the loss of instructional time impair the student's learning and hence degrade the literacy and numeracy skills, which are already appalling throughout the country. In Figure 2, we contrast the disparities in literacy and numeracy skills observed in Jammu & Kashmir across all grade levels (1-12) with those observed in the rest of India. The graph illustrates significant disparities in reading and math calculations in the education systems of all the states. In rest of India, just about 45 percent of schoolchildren in classes 1-12 can read a short story equivalent to a second-grade textbook, while only 33 percent can answer a simple division problem (three digits by one digit) comparable to a third- or fourth-grade textbook. Although the literacy rate in Jammu and Kashmir is close to the national average, the proportion of grade 1-12 students with literacy and numeracy competence is significantly lesser when compared to the other Indian states, particularly Himachal Pradesh, Punjab, and Haryana. Only about 37% and 27% of students in the state of Jammu & Kashmir can read at the second-grade level and answer mathematics problems at the third- and fourth-grade levels, respectively.

Figure 2: *Literacy and Numeracy of Students (in 1-12 grades) in Jammu and Kashmir and the Rest of India*



Note: Data Source: ASER Household Surveys from 2007-2012. Data for 2010 is not available.

Figure 3 depicts disparities in reading and math proficiency between Jammu and Kashmir and the rest of India for grades 1-12. In the graph, the horizontal line at value 1 indicates that there are no comparable disparities between the education systems of J&K and the rest of India. Any value below the line indicates that the disparities in J&K are greater than the rest of India, while any value above the line indicates that J&K is performing better in terms of reading and math proficiency. In Jammu & Kashmir, the proportion of children in grades 2-11 who cannot read a second-grade comparable textbook is significantly greater than in the rest of India, as seen in Figure 3. Similarly, the proportion of J&K students unable to solve a basic division problem is significantly higher than that of students outside of J&K. These relative discrepancies in basic literacy and numeracy skills widen until the fourth grade and then appear to close[9]. The protracted Kashmir conflict could be one of the primary explanations for these significant learning disparities.

Figure 3: *Grade Wise Literacy and Numeracy of Students (in 1-12 grades) in Jammu and Kashmir relative to the Rest of India*

Note: Data Source: ASER Household Surveys from 2007-2012. Data for 2010 is not available.

3 Data and Descriptive Statistics

Data Sources: We use several rounds of the Annual Status of Education Report (ASER) Surveys (Banerji et al., 2013), which the ASER Centre conducts in Delhi, India.

[9]Gender wise learning gaps in reading and arithmetic are also reported. See Appendix Figures A.3

The dataset is an annual national assessment of children's proficiency in reading and math calculations. These surveys have been conducted annually since 2005, producing the only uniform data on children's academic progression across India's rural districts. The ASER surveys a repeated cross-section of districts across years[10] to obtain credible estimates of children's schooling status and fundamental learning levels (reading and arithmetic) at the district level[11]. Our study's data spans five years, from 2007 to 2012, omitting 2010[12], and the data is consistently available for 13 districts of Jammu & Kashmir, encompassing all three divisions of the state (Jammu, Kashmir and Ladakh). The ASER data is distinctive because it has an enormous sample size that includes both enrolled and out-of-school children[13]. Because cognitive tests are often conducted in schools, test results must be restricted to a sample of students enrolled in school (and present when the test is given); however, ASER accommodates children aged 5 to 16 who are enrolled, have dropped out, or have never enrolled in school. For our purposes, we restrict our sample to currently enrolled students only.

The various distinct features of ASER data will be useful in our analysis. First, it is the country's largest household survey dataset encompassing roughly 580 rural districts. This allows us to capture the variation in exposure to unrest between districts while simultaneously controlling for district fixed effects, which absorb any pre-existing differences in test scores that were not caused by the unrest. Second, beginning in 2005, this survey was done annually. This allows us to capture conflict exposure across time and adjust for year-fixed effects to account for common time trends. Third, the survey gives all children between 5 and 16 these reading and math assessments, which gives us the variation in the age of students who take these tests and allows us to account for any shock common to all kids born in the same year in our analysis by controlling for birth cohort fixed effects.

Outcome Variables: The main characteristic of the dataset is the assessment of reading and math levels of all children aged five to sixteen in the sampled family. To assess the child's reading level, he began with a paragraph (of grade one level). If the child could

[10]The ASER is a representative data at the district, state and national level.

[11]In each district, 30 villages are chosen at random, and then 20 households per village are chosen at random for the survey. As a result, the sample size is 600 households per district. For more information on ASER, see http://www.asercentre.org/Overview/Basic/Pack/History/etc/p/56.html

[12]The data for year 2010 is not available for the state of Jammu and Kashmir as the surveyors could not visit J&K due to security situations.

[13]The ASER tests the children aged 5-16 in their respective homes rather than the schools they attend so as to ensure that all children are tested rather than only those who are enrolled and present in school on the day of survey.

read the paragraph, he was next asked to read a short story (of grade two level); if not, he was instructed to read any five words. If he could not read words, the child was asked to read any five letters. The child was then classified into five groups: those who could not read the letters, those who could but could not read the words, those who could read words but could not read the paragraph, those who could read a paragraph but could not read the short story, and ultimately those who could read the short story (equivalent to grade two-level). The test scores are coded as **1** if the child correctly answers the question and **0** otherwise. We generate a *"reading score"* for our purpose, the summation of the four reading questions. We code these categories by zero, one, two, three, and four.

Similarly, for arithmetic, we generate a *"math score"* variable. Children could fall into one of five categories: those who cannot recognize numbers one to nine, those who can recognize numbers one to nine but not 10 to 99, those who can recognize numbers 10 to 99 but cannot solve a simple subtraction problem (two-digit numerical problem with borrowing), those who can solve subtraction problems but not division problems (three-digit number divided by one-digit number), and finally those who can solve a division problem (equivalent to a grade 3 and 4 level textbook). These categories are denoted by zero, one, two, three, and four. The same tests were given to all the children that were tested[14].

Since these reading and math test scores take integer values only and are ordinal, to avoid any measurement errors and for the ease of interpretation of the treatment effects, we standardize these reading and math scores by subtracting the mean of any given year and dividing by the standard deviation for the same year for each observation[15]. These standardized scores serve as dependent variables in our empirical estimations. As a robustness check, we later also estimate the treatment effects using the linear probability models for each reading and math level.

Descriptive Statistics: We present the summary statistics of the key outcome variables separately for the treated and the control groups before and after the 2010 unrest

[14]The ASER provides the same tests to all children aged 5 to 16 so as to determine whether or not children have mastered early foundational reading and math skills. It is not intended to be a grade-appropriate examination, but rather to give insight into the early reading and basic arithmetic abilities of school-aged children. Although this is one shortcoming of the data, however given the current state of learning levels in India, higher grade pupils are also unable to read basic grade two level literature and solve simple arithmetic problems (see Figures 2 and 3). For further details, see Muralidharan et al. (2019)

[15]The variables are standardized such that the mean and standard deviation in any given year is 0 and 1 respectively.

in Table 1. The proportion of students exposed to the conflict-induced school closures who can read letters, words, para and story was lower in the post-2010 unrest period. On the contrary, the proportion of non-exposed students able to read at different levels was higher in the post-conflict period. Similarly, the proportion of impacted students who can recognize single-digit numbers, double-digit numbers, and solve subtraction and division problems was also lower in the post-period, but there were no significant changes in the post-period for the control group. While the reading score has shown improvement in general, the control group has made greater progress than the treated group. Similarly, the magnitude of reduction in math score is relatively larger for the treated group. Before and after the unrest, the average reading and math score for both the control and treated groups was roughly 3. Given the ordinal nature of these test score variables, this number indicates that, on average, students can read at the grade 1 difficulty level not at the grade 2 difficulty level; they can solve problems at the grade 3 difficulty level but not at grade 4 level. The descriptive statistics of other important variables used in this study are reported in Table A.1. The means of the control and treated groups are comparable on individual, household and village level characteristics.

Children's learning levels are relatively low, as shown in Figure 4. Only approximately 38% of the children tested could read a short story equal to a grade two level textbook, while only 22% of the children can read a paragraph, equivalent to a grade one text, but they cannot read a story. Together, 60 percent of the pupils in the sample can read a text at the grade one level. Further, only just about 20% of pupils can read words and not a grade one level comparable material, and around 4 percent of students cannot read even a single letter. Regarding math exams, whereas 28 percent of students can solve division problems evaluated at the textbook level of class 4, just approximately 29 percent can handle simple subtraction problems at the difficulty level of class 3. In sum, 57 percent of those tested can solve simple arithmetic problems at the level of class 3; however, just 26% of all tested children can recognize a two-digit number, while they can also not solve a subtraction problem.

4 Econometric Model

In this paper, we examine the implications of a violent but unprecedented civilian unrest that killed over 100 civilians, causing school shutdowns for about 4 months due to safety concerns and a heightened threat to life. Our identification strategy exploits variation in exposure to conflict across districts and time to determine the effect of an individual's

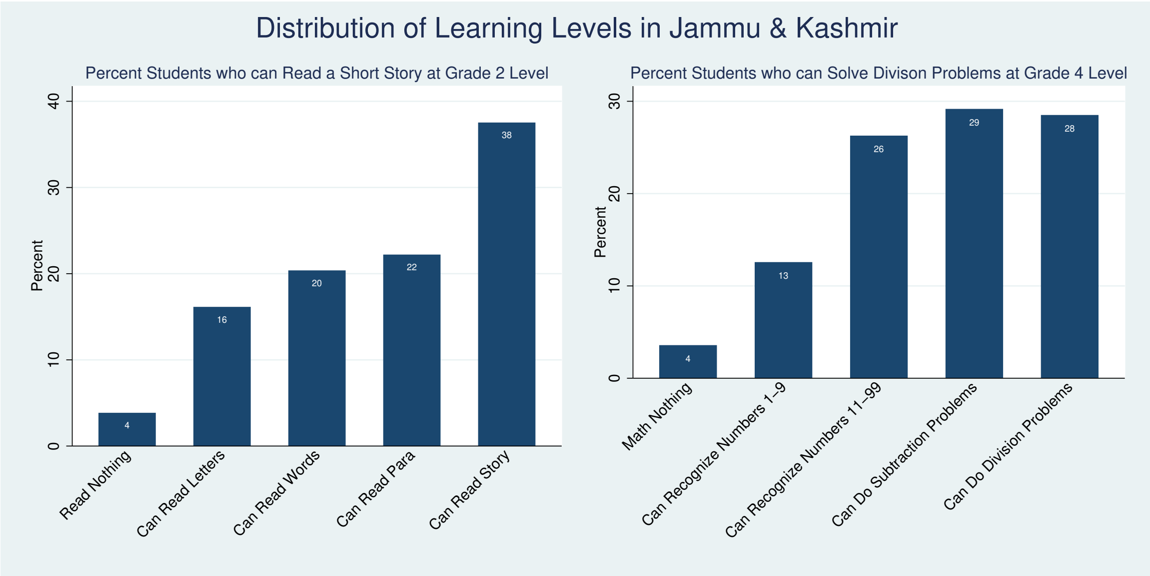
Table 1: *Descriptive Statistics of Outcome Variables*

	Control Group		Treated Group	
	Pre-Unrest Mean (SD)	Post-Unrest Mean (SD)	Pre-Unrest Mean (SD)	Post-Unrest Mean (SD)
Can Read Letters	0.79	0.79	0.87	0.75
	(0.41)	(0.41)	(0.34)	(0.44)
Can Read Words	0.65	0.65	0.74	0.61
	(0.48)	(0.48)	(0.44)	(0.49)
Can Read Para	0.47	0.52	0.53	0.49
	(0.50)	(0.50)	(0.50)	(0.50)
Can Read Story	0.29	0.34	0.33	0.32
	(0.45)	(0.47)	(0.47)	(0.47)
Reading Score	2.68	2.81	2.74	2.79
	(1.22)	(1.24)	(1.20)	(1.26)
Can Recognize Numbers 1-9	0.78	0.78	0.86	0.75
	(0.41)	(0.41)	(0.34)	(0.44)
Can Recognize Numbers 11-99	0.68	0.68	0.76	0.65
	(0.47)	(0.47	(0.43)	(0.48))
Can Do Subtraction Problems	0.48	0.46	0.54	0.42
	(0.50)	(0.50)	(0.50)	(0.49)
Can Do Division Problems	0.25	0.22	0.27	0.16
	(0.44)	(0.41)	(0.45)	(0.36)
Math Score	2.70	2.64	2.72	2.54
	(1.14)	(1.11)	(1.13)	(1.06)

Note: The outcome variables, except reading and math scores, are all binary variables that take value **1** if Yes and **0** if No. Reading and Math scores take values from 0-4. Treated group comprises all the districts of Kashmir while control group comprises the districts Rajauri, Jammu, Leh(Ladakh), and Kargil. Pre and Post-unrest are the periods before and after 2010 unrest. Data Source: ASER Household Surveys from 2007-2012. Data for 2010 is not available.

exposure to civil unrest on learning outcomes. Ideally, we would like to compare the test score outcomes of the affected students in the Kashmir valley with those in the Jammu and Ladakh provinces before and after the unrest under the difference-in-differences (DID) framework. However, since the identification of treatment effects under DID relies on the '*parallel trends*' assumption, the districts not impacted by the conflict may be sys-

Figure 4: *Distribution of Learning Levels of Students in Jammu & Kashmir*



Note: Data Source: ASER Household Surveys from 2007-2012. Data for 2010 is not available.

tematically different from those districts where the conflict is concentrated, and there may be spillover effects of the conflict in neighbouring districts, causing parallel trends not to hold. To reduce such confounding, we first find the optimal mix of the districts that are not impacted by the 2010 mass unrest to serve as the counterfactual group for the impacted districts using the synthetic control method (SCM) (Abadie, 2021; Abadie et al., 2010; Abadie & Gardeazabal, 2003). Later, under the DID framework, we take all those unaffected districts as our comparison group, which receive the greatest weight in constructing the optimal counterfactual group by the SCM and which do not largely share the boundaries with Kashmir to rule out the spillover effects of violence.

In a DD framework, we specifically estimate the model of the following specification separately for both the reading and math assessments;

$$Y_{idt} = \beta_0 + \beta_1 Kashmir_{id} \times Post_t + \gamma X_i + \lambda H_{idt} + \psi Z_{idt} + \phi_d + \delta_t + \theta_b + \epsilon_{idt} \qquad (1)$$

where Y_{idt} is the test score outcome of individual i residing in district d in the ASER survey year t. The test scores Y_{idt} are standardized by year[16]. *Post* is a dummy variable that identifies the children i who are surveyed after the 2010 unrest and takes value **1** for the post-unrest years 2011 & 2012 and **0** for the pre-unrest years 2007, 2008 & 2009. *Kashmir* is an indicator variable that takes a value of **1** for the districts of Kashmir

[16] The test scores are standardized in order to avoid measurement errors and to compare them across time. We have standardized the test score by subtracting the mean of any given year and dividing by the standard deviation for the same year for each individual observation.

valley and **0** for the districts in the Jammu and Ladakh regions of the state. Note that these indicator variables are not included in the regressions because their impacts are subsumed in the year and district fixed effects, respectively. The variable of interest is the $Kashmir \times Post$ which represents the districts of Kashmir valley in the post-2010 unrest period. The coefficient of interest β_1 accounts for any differences in test scores between students from Kashmir and non-Kashmir districts due to the 2010 violence. We add a number of control variables to our specification to reduce the bias due to omitted variables. Following Bellows & Miguel (2009), we evaluate the relative impact of the omitted variable bias by analyzing how the coefficient of interest changes when the additional explanatory factors are taken into account. Selection into violence is unlikely to be driving our main results if the presence of additional controls has no impact on the magnitude of the estimated coefficient. $\mathbf{X_i}$ is a vector of student-level covariates that vary across individuals. We control for the child's gender and grade in which the student is enrolled at the survey time. $\mathbf{H_{idt}}$ and $\mathbf{Z_{idt}}$ are the vectors of household and village covariates that vary across individuals, districts, and time. The household-level controls include household size, parental education, the type of household[17], and whether the household has an electricity connection and mobile. Village level controls include whether the village has electricity, a *pucca* (concrete) road and a ration shop.

4.1 Threats to Identification

Our identification strategy relies on the assumption that, in the absence of the unrest, the exposed cohort of children taking ASER tests in the post-conflict years would have followed the same trend in terms of test score outcomes as the unexposed cohort. Besides using the set of unaffected control districts that replicate the affected districts pretty well in the pre-intervention period, we perform a falsification test to check whether the *'parallel trends'* assumption holds. Specifically, we run the DD model by reassigning the post-conflict year to 2008, and if any prior trends do not drive our results, then the coefficient on the interaction term in the DD model should not be statistically or economically significant.

[17]Since the ASER survey is mostly about testing children, there isn't much information about income (Chakraborty & Jayaraman, 2019). Still, surveyors do record some indicators of wealth. The type of housing is the most important of these. This includes a record of what a house is made of. *"Pucca"* stands for a house made of strong materials, like brick, stone, or cement. *"Kutcha"* stands for a house made of less strong materials, like mud or bamboo. *"Semipucca"* stands for something in between. So, a student from a pucca (concrete) house is supposedly expected to come from a high-income family.

Despite controlling for the district and year fixed effects in our baseline model to account for existing trends in the test score outcome variables, we may still be concerned that the timing of the unrest is correlated with trends in test scores across districts. As a robustness check, we account for this by including the *district-specific linear time trends* in our model. We also include the *district* × *birth-year* fixed effects as a robustness check to account for district-specific insurgency-related events and other early-life shocks that may differ between districts and student cohorts. For instance, the 1999 India-Pakistan war may have had a greater impact on students born in the Ladakh region during the war than on kids from other districts.

The other potential concern with our identification strategy may be the endogeneity issue. It may be possible that the conflict is likely endogenous, so that the group of the students who are exposed to these violent conflicts may be systematically different from other non-exposed groups. Although we generate the control group for our difference-in-differences strategy using the synthetic control method that closely mimics the path of the treatment group concerning the outcome variables, as a robustness check, we use a different identification strategy called propensity score matching (Rosenbaum & Rubin, 1983) to identify the effect of the conflict on reading and math test performance. We have been assuming until now that the treated and control groups have similar distributions and are thus comparable. If that does not hold, the estimated effects are likely to be biased. To this end, we take a step forward and use the propensity score matching and the coarsened exact matching (Blackwell et al., 2009) techniques. This entails matching individuals that are identical on observable characteristics at the baseline. We combine the kernel propensity score matching technique with the difference-in-differences (KSPM DD) method (Blundell & Dias, 2009; Heckman et al., 1997, 1998) and the coarsened exact matching (CEM) with the difference-in-differences (CEM DD).

5 Results

5.1 Synthetic Control Analysis

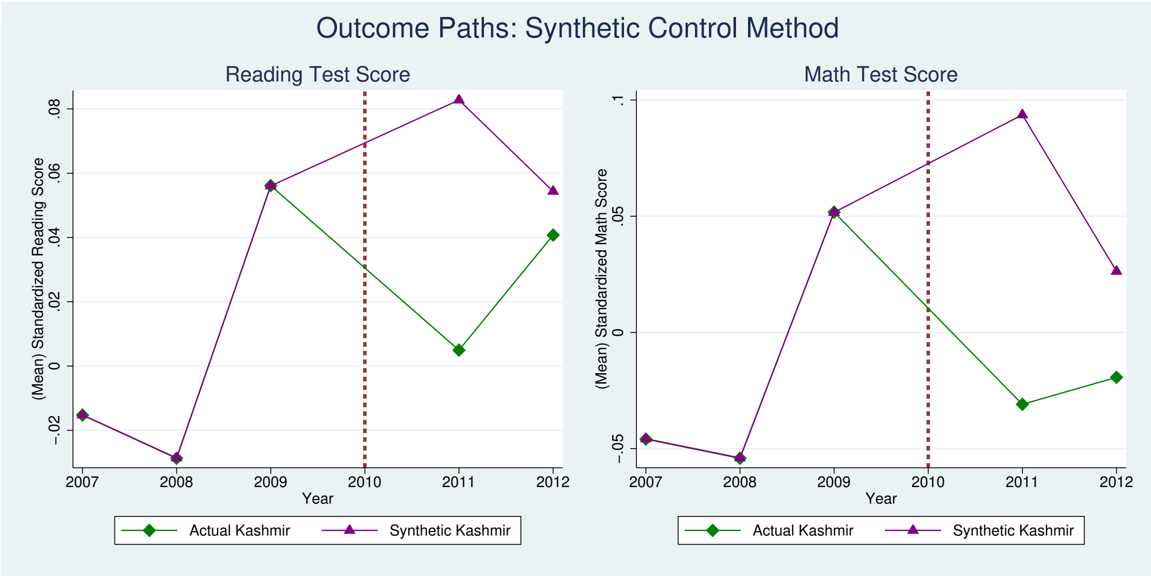
The synthetic control analysis requires a balanced panel of aggregate units (e.g., counties, states, or districts), one of which receives an intervention while the others serve as the donor pool of counterfactuals. We merge all of the treated districts into one first and average out the variables over the years to generate a balanced panel at the district level because we do not have access to panel data and more than one district is simultaneously impacted by the conflict. As a result, the outcome variables in our synthetic control estimations are standardized test scores in reading and math, averaged over districts and years, and the treatment effects from the SCM are therefore at the aggregate level. Appendix Table A.2 shows the control weights separately for reading and math exam scores[18]. For mathematics, Rajauri, Jammu, Leh(Ladakh), and Kargil receive the highest weights in constructing the synthetic Kashmir whose weights are 0.415, 0.141, 0.136 and 0.133, respectively. For reading, the Leh(Ladakh) district in the Ladakh division receives a weight of 0.566, followed by Kargil and Kathua, which receive a weight of 0.146 and 0.11, respectively and the other districts in the donor pool receive more or less identical weights. Appendix Table A.3 shows the balance of the predictor variables used to build the synthetic version for the districts of Kashmir valley using the SCM. These predictor values indicate how well the weighted mixture of donor districts resembled the districts of Kashmir prior to the 2010 conflict; the synthetic Kashmir seems comparable to the actual Kashmir by examining the balance of predictors at the baseline. Figure 5 depicts the treated units' actual and synthetic paths from 2007 to 2012. During the pre-2010 unrest period, 2007-2009, the actual and the synthetic Kashmir behaved identically. This is encouraging about the Synthetic Kashmir's quality as a counterfactual to the actual Kashmir. From 2010 onward, when the 2010 mass unrest occurred, the two paths diverged; Kashmir took values around 0.08 standard deviation less in reading and 0.12 standard deviations lower in math than the synthetic Kashmir in 2011. These adverse effects persisted in 2012, but they reverted to synthetic Kashmir's path. Since the treatment effects are given by the differences in the actual and the synthetic paths, the treatment effect for years prior to the intervention is zero because the Kashmir and synthetic Kashmir paths completely overlap. However, following the 2010 conflict, the two paths diverge, and learning deficits emerge. Next, in Appendix Table A.4, we present the treatment effects[19] with inference measures from the synthetic control method. The effects of the post-treatment periods are adverse and significant to the standardized effect measure showing that the 2010 conflict likely negatively impacted students' reading and math scores in Kashmir districts. We present the other results from the synthetic control analysis in Appendix[20].

[18]The weights are determined in Stata using the *synth* package (Abadie et al., 2010)

[19]These treatment effects and the accompanying inference measures were derived using the *synth_runner* package in Stata (Galiani & Quistorff, 2017)

[20]See Figures A.4-A.9

Figure 5: *Outcome Paths: Synthetic Control Method*



Note: Outcome variables are the standardized test scores on reading and math exams averaged over districts and years. The figure is generated in Stata using the command *synth_runner*. Data Source: ASER Household Surveys from 2007-2012. Data for 2010 is not available.

5.2 Difference-in-Differences Analysis

We will now present the results from our preferred difference-in-differences specification to determine the Intent-to-Treat (ITT) effects at the individual level, the heterogeneity analysis and possible underlying mechanisms. We use the districts in Jammu and Ladakh divisions that receive the greatest weights in the synthetic control analysis as our control group. Because the adverse treatment effects of SCM on mathematics are severe, we construct the control group using the top four districts that acquire the most weight in mathematics. Specifically, districts Rajauri, Jammu, Leh(Ladakh) and Kargil serve as our control group in the DD estimation regressions[21]. Our main results for math are not sensitive to the inclusion of other low-weight neighboring districts as controls, but our main results for reading are very sensitive to this. This suggests that spillover effects of violence may explain away the treatment effects in reading. Furthermore, to use all the available data, we specify the *Post* dummy in our DD specification as taking a value **1** for all the post-conflict years and **0** for all the pre-conflict years[22].

[21] The choice of these districts is based also on the fact that these districts do not largely share boundaries with Kashmir districts which allows us to rule out the spillover effects of violence. Besides, these districts are quite similar in terms of literacy and poverty rates. See Figure 1 Panel B for the information on the treatment status of each district.

[22] Specifically, *Post = 0* for years 2007, 2008 and 2009 and *Post = 1* for years 2011 and 2012.

The regression results from our baseline specification (1), in which we use the standardized reading and math scores as the dependent variables, are shown in Table 2. Each model contains the district, survey-year and birth-year fixed effects to account for the unobserved district, survey-year and birth-year heterogeneity. The estimated coefficient on the interaction term $Kashmir \times Post$ is of interest in these regressions which yields the Intent-to-Treat (ITT) effects. The results in this table reveal that the conflict had a negative and statistically significant impact on student performance in reading and math exams in nationwide standardized ASER tests. The negative effect of conflict on performance in reading and math is robust to the inclusion of several control variables. We add a set of individual level controls in columns (2) and (6), including the student's gender, and grade. We also add a set of household-level controls in columns (3) and (7) to adjust for time-varying household economic factors, such as household size, parental education, indicators for the type of dwelling, electricity connection, and mobile. Finally, we add a vector of village-level controls in columns (4) and (8), including electricity, road, and ration shop availability indicators to adjust for time-varying local economic conditions[23]. The sign and significance of conflict's impact on test performance in reading and math exams remain statistically significant. Note that the treatment effects actually increase in magnitude when we introduce a set of individual, household, and village-level control variables in our specification. So, if we follow the reasoning of Bellows & Miguel (2009), it is very unlikely that the omitted variable bias explains away our treatment effects.

The estimated coefficient on the interaction term between Kashmir and Post is negative and statistically significant for test scores. We find a negative effect of about 0.13 standard deviations on reading (Table 2: column 4) and 0.22 standard deviations on math scores (Table 2: column 8). Our finding that the shock to schooling resulting from the conflict has a relatively smaller effect on reading performance and a larger effect on the math achievements is consistent with the existing literature. The general finding in the literature is that educational inputs and policies, as well as the conditions in the learning environment, have a more significant impact on math exam performance (for instance, see Abadía Alvarado et al. (2021); Aucejo & Romano (2016); Gershenson & Tekin (2018); Hanushek & Rivkin (2010); Monteiro & Rocha (2017)). This might be because children are more likely to be exposed to reading and literacy outside of school, particularly at home, where parents are more likely to help their children acquire and

[23]We lose a significant number of observations after controlling for the important household and village control variables. Since the most of this background information was collected after 2009, the treatment effects in columns 3, 4, 7 and 8 are estimated using only one of the three pre-intervention years as opposed to all three. Nonetheless, the addition of these background variables does not significantly alter our results qualitatively.

Table 2: *Effect of conflict on the student performance in reading and math exams on nationwide standardized tests for students of Kashmir during 2010 unrest: Intent-to-Treat Effects*

	Standardized Reading Score				Standardized Math Score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Kashmir × *Post*	-0.09**	-0.07	-0.12*	-0.13*	-0.14***	-0.12***	-0.22***	-0.22***
	(0.04)	(0.04)	(0.07)	(0.07)	(0.04)	(0.05)	(0.08)	(0.08)
Constant	0.90***	0.15	-0.77***	-1.06***	0.81***	0.09	-0.99***	-1.24***
	(0.06)	(0.13)	(0.15)	(0.24)	(0.07)	(0.14)	(0.14)	(0.21)
Individual Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes	No	No	Yes	Yes
Village Controls	No	No	No	Yes	No	No	No	Yes
Observations	46,621	40,759	5,682	5,547	46,267	40,489	5,640	5,506
R-Squared	0.45	0.43	0.49	0.49	0.42	0.40	0.47	0.48
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Kashmir is a treatment dummy taking value **1** for districts in Kashmir valley and **0** for districts Rajauri, Jammu, Leh(Ladakh), and Kargil. *Post* dummy takes value **1** for post-unrest years 2011 & 2012 and **0** for pre-unrest years 2007, 2008 & 2009. Outcome variables reading score and math score are standardized by year such that the mean and standard deviation for each year is 0 and 1, respectively. Individual controls include the gender and grade of the child. Household controls include household size, parental education and indicators for the type of dwelling, household electricity connection & mobile. Village controls include the dummies for electricity, road and ration shop availability. The treatment effects in columns 3, 4, 7 and 8 are estimated using only one of the three pre-intervention years as opposed to all three because the important household and village level information is collected from 2009. Robust standard errors clustered at the village in parentheses. Data Sources: ASER Household Surveys from 2007-2012. Data for 2010 is not available. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

develop reading skills (Currie & Thomas, 2001). Another explanation concerns the opportunities to practice academic content during the school breaks. According to Cooper et al. (1996), children may practice reading outside of the classroom and do not require instructor supervision. During school absence, students may practice reading comprehension, grammar, and vocabulary independently, but students do not have as much access to math calculation and problem-solving practice as they would like, which necessitates the assistance of a teacher or tutor.

Appendix Table A.5 shows that our main results do not largely change when we deviate from our preferred specification (Table A.5: columns 4 and 8) and exclude the fixed effects for the district, survey year, and birth year. The negative impact rises when we remove the birth-year and survey-year fixed effects from our preferred specification (Table A.5: columns 2, 3 and 6, 7). However, when the district fixed effects are removed, the coefficient on the interaction term in column 1 has the expected negative sign but is not statistically significant.

Overall, according to our preferred specification (1), we find that the civil unrest of 2010 had a detrimental effect on the reading and math performances of the exposed cohorts. The loss of learning associated with conflict is 0.13 standard deviations in reading and 0.22 standard deviations in math. Interpreting these effect sizes, however, is not a straightforward task. Although a small effect in student learning is defined as 10% of a standard deviation (Cohen, 2013), it is better understood by comparing it to empirical standards relevant to the situation under investigation (Hill et al., 2008). Compared to a few closely related studies examining the impact of conflicts on student achievement in examinations, these treatment effects are quite large. For example, Monteiro & Rocha (2017) find a 0.054 standard deviation reduction in math test performance but no effect on reading performance for students exposed to drug-related violence in Brazil. Michaelsen & Salardi (2020) discover that drug-related violence during a week before the tests (at least three homicides) in Mexico is associated with a 0.1 standard deviation drop in exam scores. In Colombia, Gómez Soler (2016) finds adverse effects in the range of 0.15 standard deviations in math and 0.08 standard deviations in language using the pseudo panel estimation. In Brazil, Koppensteiner & Menezes (2021) show that an additional homicide within a 25-meter radius of the school affects test scores in math and language by roughly 0.05 standard deviations. Further, Brück et al. (2019) find that one standard deviation increase in the number of fatalities in the Israeli–Palestinian conflict reduces the math and language test scores by 0.03 and 0.02 standard deviations, respectively while conflict in Turkey reduces the university math entrance test scores by 0.014 points (Kibris, 2015).

In an Indian context, after five years of programme exposure, Muralidharan & Sundararaman (2011) show that delivering individual-level performance bonuses to instructors in India resulted in test score improvements of 0.54 standard deviations and 0.35 standard deviations in math and language, respectively. Banerjee et al. (2007) find that after two years of a math computer-assisted learning programme, primary-school students in urban India scored 0.47 standard deviations higher in math, while after 4.5 months of targeted technology-aided after-school tutoring, middle school students scored 0.36 standard deviations better in arithmetic and 0.22 standard deviations higher in Hindi (Muralidharan et al., 2019). These estimates suggest that the students in India learn at a slower pace. Thus, compared to these studies also, our estimates are larger in magnitude.

5.2.1 Heterogeneity Analysis & Possible Underlying Mechanisms

Conflict may affect students' test scores indirectly via several channels. Unrest may impact school resources, such as increased absenteeism, lost instructional time, or school closures or may directly impact learning via mental and psychological health channels. Additionally, students might drop out of school due to reduced household resources or the threat of direct bodily damage because of violence, all of which may impact student performance. We present heterogeneity results in Tables 3, 4 and 5 to identify vulnerable groups and explore possible channels via which conflict might have impacted students' test scores. Understanding the heterogeneous effects of violence in Kashmir might also help policy discussions by identifying disproportionately impacted sub-groups. For each outcome variable, reading and math test score, we show the main results from our preferred specification and use triple interaction with student's grade level, gender, socioeconomic status, and school type. Additionally, we investigate the heterogeneous treatment effects along the test scores distribution.

Grade Level: Table 3 presents the treatment effect heterogeneity for students in elementary, middle, and secondary grades. The main results from our baseline specification are reported in columns 1 and 4 and in columns 2, 3, 5 and 6 we interact the DD coefficient with the grade-level dummy variables[24]. We find no evidence that the 2010 unrest affected reading or math scores for elementary school students (Table 3: row 1, columns 2, 3 and 5, 6). The unrest has negatively impacted the test scores of upper-grade students, who drive the main results. Compared to the primary school students, middle school students in grades 6-8 are the worst affected, with -0.32 and -0.31 standard deviation losses in reading and math, respectively and the high school children in 9-12 grades are also severely impacted, and the differences are statistically significant. We do not find any impact of conflict on the younger children because parents may help primary school students study during school closings since they are too young and easy to oversee at home and the inability to homeschool the relatively elder children coupled with long absences from school cause learning losses for the middle and high school students[25].

[24]Middle dummy variable takes a value 1 for middle school children in grades 6-8 and 0 for primary school children in grades 1-5. High dummy variable takes a value 1 for high school children in grades 9-12 and 0 for primary school children in grades 1-5.

[25]This finding is consistent with results from the Bosnain War, in which exposure to the war is associated with a lower likelihood of completing secondary schooling but has no effect on primary schooling (for details, see Swee (2015)).

Table 3: *Heterogeneity in the Treatment Effects of Violence by Grade Levels*

	Standardized Reading Score			Standardized Math Score		
	(1)	(2)	(3)	(4)	(5)	(6)
Kashmir × *Post*	-0.13*	-0.01	0.05	-0.22***	-0.12	-0.07
	(0.07)	(0.09)	(0.08)	(0.08)	(0.10)	(0.09)
Middle		-0.18***			-0.18***	
		(0.05)			(0.05)	
Kashmir × *Post* × *Middle*		-0.32***			-0.31***	
		(0.05)			(0.05)	
High			-0.89***			-0.80***
			(0.08)			(0.09)
Kashmir × *Post* × *High*			-0.24***			-0.21***
			(0.06)			(0.07)
Constant	-1.06***	-1.73***	-1.10***	-1.24***	-1.63***	-1.28***
	(0.24)	(0.55)	(0.25)	(0.21)	(0.45)	(0.22)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes
Village Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,547	4,556	4,106	5,506	4,514	4,072
R-Squared	0.49	0.48	0.52	0.48	0.46	0.51
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: See Table 2 Notes. The primary sample consists of students in grades 1-5 and middle and high school students in grades 6-8 and 9-12, respectively. Middle and High dummy variables take value **1** for middle and high school students respectively and **0** for primary school students. Robust standard errors clustered at the village in parentheses. Data Sources: ASER Household Surveys from 2007-2012. Data for 2010 is not available. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Our finding that the conflict-induced school closures negatively impact the literacy and numeracy skills of middle and high school students is significant in the conflict literature. Although Brück et al. (2019) discover a negative and significant impact of the Israeli-Palestinian conflict on the arithmetic test performance of high school students, they use grade-appropriate final exam results as the outcome variable. On the contrary, our paper adds to the limited research on conflict's severity. Insofar as these students benefit from classroom instruction and their parents cannot teach them at home, Table 3 suggests that school shutdown is likely the channel through which the conflict affected student test scores. We provide more suggestive evidence of this mechanism below.

Test Scores Distribution: The individual and cross-country differences in incomes and economic well-being may be partly attributed to educational inequalities (Hanushek & Woessmann, 2011; Rodríguez-Pose & Tselios, 2009). If protracted and recurring conflicts affect various cohorts differently, they could further exacerbate educational inequality within the affected regions and have serious long-term consequences. For example, suppose conflicts exclusively affect low-performing cohorts of students and have no effect on high-performing cohorts. In that case, more impacted cohorts will have fewer opportunities to attain a decent and high-paying job that demands superior abilities, resulting in future economic inequalities.

Using the quantile regression model[26], we investigate the heterogeneity of treatment effects along the test scores distribution in Table 4. In column 1, we present our main results for each test score variable in panels A and B. The quantile regression results in columns 2-8 show that the conflict affects up to the median of the test score distribution but not the quantiles above the median, for which the conflict has no significant and, more importantly, economically meaningful impacts. According to the quantile regression results, the conflict, while lowering the test scores of the impacted cohorts in general (Table 2) and middle and high school students in particular (Table 3), does not affect students in the upper tail of the test scores distribution. This result suggests that the mechanisms behind the impact of conflict on student test scores affect low-performing students primarily. As a result, we may rule out more direct underlying mechanisms such as harm to school infrastructures, degradation of psychological and mental well-being, the threat of direct bodily damage, etc., which should affect both the low and high-performing students.

Gender: Gender disparities in treatment effects for conflict are well documented[27]. Violent conflicts often have gender disproportionate effects on educational attainment through direct pathways such as infrastructure destruction, loss of livelihood, and direct bodily danger (Bharati, 2022). If the conflict affects household income, for example, the households might change the gender resource distribution which generally favours boys in Asia (Maccini & Yang, 2009) and particularly in India (Roy & Singh, 2016; Singh & Shemyakina, 2016). Conflict can also affect educational outcomes if there is a threat of

[26] For the details of quantile regression models, see Koenker & Hallock (2001)

[27] See Brück et al. (2019); Roy & Singh (2016); Singh & Shemyakina (2016); Valente (2014); Blattman & Annan (2010); Buvinić et al. (2014); Chamarbagwala & Morán (2011); Dabalen & Paul (2014); Diwakar (2015); Shemyakina (2011).

Table 4: *Heterogeneous Treatment Effects of Conflict Along Test Score Distribution in Reading and Math*

	OLS	Quantile Regression						
	Full Sample	5th	10th	25th	50th	75th	90th	95th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Standardized Reading Score								
Kashmir × *Post*	-0.13*	-0.28*	-0.20*	-0.20***	-0.02*	-0.00***	-0.00	-0.00**
	(0.07)	(0.14)	(0.10)	(0.04)	(0.01)	(0.00)	(0.00)	(0.00)
Constant	-1.06***	-3.06***	-1.81***	-1.55***	0.80***	0.97***	0.97***	0.97***
	(0.24)	(0.46)	(0.29)	(0.25)	(0.13)	(0.00)	(0.00)	(0.00)
Observations	5,547	5,547	5,547	5,547	5,547	5,547	5,547	5,547
Panel B: Standardized Math Score								
Kashmir × *Post*	-0.22***	-0.21***	-0.37***	-0.33***	-0.30***	0.00	0.00	-0.00***
	(0.08)	(0.06)	(0.09)	(0.07)	(0.05)	(0.06)	(0.00)	(0.00)
Constant	-1.24***	-2.03***	-2.06***	-1.65***	-1.13***	1.04**	1.04***	1.04***
	(0.21)	(0.34)	(0.24)	(0.26)	(0.22)	(0.46)	(0.00)	(0.00)
Observations	5,506	5,506	5,506	5,506	5,506	5,506	5,506	5,506
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: See Table 2 Notes. Robust standard errors clustered at village in parentheses for column 1 and Bootstrap standard errors in parentheses for columns 2-9. Data Sources: ASER Household Surveys from 2007-2012. Data for 2010 is not available. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

immediate physical damage like threat of women being abducted and raped (Shemyakina, 2011; Singh & Shemyakina, 2016) and kidnapping or conscription of men (Valente, 2014; Blattman & Annan, 2010).

Table 5 shows gender heterogeneity results. In columns 1 and 5, we show the main results and use triple interaction term with a gender dummy in columns 2 and 6. We find no gender difference in reading, but female students do worse on math tests. In rural areas, females may be required to help with the housework, leaving them with less time to practice mathematics at home than boys. Thus, we observe a significant differential effect for girls in math only but not in reading. We find no substantial increase in the likelihood of students dropping out post-conflict nor any significant differences for female students (see Table A.6). Therefore, the direct pathways like physical dangers or resources constraints are unlikely to be the underlying mechanisms.

Socioeconomic Status: Students from low-income families or low socioeconomic backgrounds may be disproportionately impacted by learning disruptions. For instance, Shemyakina (2011) finds that violent conflicts reduce the likelihood of impoverished children attending school, but Akresh & de Walque (2008), on the contrary, find that non-poor families were more affected by the Rwandan genocide. In Table 5, columns 3 and 7, we show how 2010 unrest in Kashmir affected student achievement based on socioeconomic status. We interact the difference-in-differences interaction term with a dummy for a child's type of dwelling[28] and do not find any differential impact of violence on the non-poor student test-takers. Non-poor kids do not benefit. The differential effect is moderating but is not statistically significant. This finding further suggests that the income is not at work in since our results show that being from a relatively well-off family does not matter.

School: The evidence of private school advantage in the Indian setting is well documented[29] and the general belief is that students in private schools have superior educational achievements to those in public schools. Furthermore, studies show that low-performing children are the ones who suffer the most from school disruptions[30]. We examine treatment effect heterogeneity based on the kids' school type. We present the results in Table 5, columns 4 and 8, where we interact the DD coefficient with a dummy for the type of school the child attends. The results show that private school students are significantly less affected by violence. The conflict affects low-performing government school kids relatively more. This result also suggests that the conflict might have affected students' performance through the school closure channel. Given the already dismal performance of government school students, the loss of instructional time will only worsen their performance.

[28] We proxy for income by the kind of the residence a student lives in at the time of the survey because we do not have data on the income available in ASER. Thus, a student from a *pucca* (concrete) house is supposedly expected to come from a high-income family, whilst those from *non-pucca* households (*kutcha* or *semi-kutcha*) are presumed to come from a lower-income family.

[29] See Chudgar & Quin (2012); Goyal (2009); Muralidharan & Kremer (2006); Singh & Sarkar (2015)

[30] For instance, Aucejo & Romano (2016) find that school absences hurt low-achieving kids while government school children are more affected by violence in West bank (Brück et al., 2019)

Table 5: *Heterogeneity in the Treatment Effects of Violence by Gender, Socioeconomic Status and Type of School*

	Standardized Reading Score				Standardized Math Score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Kashmir × *Post*	-0.13*	-0.15*	-0.17**	-0.24***	-0.22***	-0.27***	-0.26***	-0.29***
	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)
Male		-0.02				0.03		
		(0.02)				(0.02)		
Kashmir × *Post* × *Male*		0.05				0.10**		
		(0.04)				(0.04)		
Non-Poor			0.05*				0.11***	
			(0.03)				(0.03)	
$Kashmir \times Post \times Non-Poor$			0.08				0.06	
			(0.05)				(0.06)	
Private				0.27***				0.30***
				(0.03)				(0.04)
Kashmir × *Post* × *Private*				0.17***				0.10*
				(0.05)				(0.06)
Constant	-1.06***	-1.05***	-1.03***	-1.05***	-1.24***	-1.22***	-1.22***	-1.25***
	(0.24)	(0.24)	(0.23)	(0.24)	(0.21)	(0.21)	(0.21)	(0.22)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,547	5,547	5,547	5,504	5,506	5,506	5,506	5,463
R-Squared	0.49	0.49	0.49	0.51	0.48	0.48	0.48	0.50
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: See Table 2 Notes. Male is a dummy taking value **1** for male students. Similarly, the Non-Poor dummy takes a value of **1** for students who reside in concrete made houses, and the Private dummy takes a value of **1** for the private school students. Robust standard errors clustered at the village in parentheses. Data Sources: ASER Household Surveys from 2007-2012. Data for 2010 is not available. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6 Robustness Checks

This section shows that our main results hold up to a variety of specification checks. Although we constructed the control group using the synthetic control method, to lend further credence to the plausibility of common trends assumption, we perform a falsification test or control experiment, where we estimate our baseline model by resetting the post-treatment status to the year 2008. The coefficient on the interaction term in the DD model should not be statistically or economically significant, if our results are not driven by any prior trends and any shocks or other policies contemporaneous with the conflict that affect different cohorts differently. The results of this falsification test are presented in Table 6. We do not find any statistically and economically significant effect, suggesting that the treatment and control districts followed similar paths in the pre-conflict period.

Table 6: *Falsification Test: Parallel Trends Assumption*

	Standardized Reading Score				Standardized Math Score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Kashmir	0.08				-0.04			
	(0.09)				(0.07)			
Pseudo-Post	0.04	0.02			0.02	0.03		
	(0.07)	(0.07)			(0.07)	(0.07)		
$Kashmir \times Pseudo-Post$	-0.11	-0.03	-0.03	-0.04	-0.02	-0.00	-0.00	-0.01
	(0.11)	(0.10)	(0.10)	(0.11)	(0.09)	(0.09)	(0.09)	(0.09)
Constant	-1.93***	-1.74***	-1.74***	0.07	-2.01***	-2.03***	-2.03***	-0.07
	(0.11)	(0.13)	(0.13)	(0.15)	(0.12)	(0.14)	(0.14)	(0.14)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,165	5,165	5,165	5,165	5,158	5,158	5,158	5,158
R-Squared	0.41	0.43	0.43	0.44	0.45	0.45	0.45	0.48
District FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Birth-Year FE	No	No	No	Yes	No	No	No	Yes

Note: See Table 2 Notes. *Pseudo-Post* dummy takes value **1** for the pre-unrest year 2008 and **0** for the pre-unrest year 2007. Controls include child's age, gender, grade, mothers' education and household size. Robust standard errors clustered at the village in parentheses. Data Sources: ASER Household Surveys from 2007-2012. Data for 2010 is not available. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We may be concerned that the timing of the unrest might be correlated with trends in test scores across districts and that students born in different districts might have different exposure to early life shocks. To account for such confounding factors, we include the *district* $\times$ *birth-year* fixed effects and the *district-specific linear time trends* in our baseline specification (1). Appendix Table A.8 presents the results where the main results are reported in columns 1 and 5, and the district $\times$ birth-year fixed effects and time trends are included in the other columns for each outcome variable, reading and math test scores. When we add the district $\times$ year of birth fixed effects, our treatment effects are still statistically significant and slightly increase in magnitude. However, when we take into account the linear time trends for each district, the estimates for both outcome variables go up by a significant margin, but qualitatively our results stay the same. So, if we do not consider time trends in our preferred specification, at best, we might be underestimating the true effects of violence on test scores.

Regarding the endogeneity or the sample selection issues, we use a different identification strategy called propensity score matching (Rosenbaum & Rubin, 1983) in conjunction with the difference-in-differences to identify the effect of the conflict on reading and math test performance. This entails first matching individuals that are identical on observable characteristics and later estimating the DD model on the matched sample. We combine the kernel propensity score matching with the difference-in-differences (KSPM DD)[31] (Blundell & Dias, 2009; Heckman et al., 1997, 1998). We match the treatment and control units at the baseline on child's age, gender, grade and parental education using probit model. We limit the kernel weights to the common support of the propensity score for the treatment and control groups to improve the estimand's internal validity. Furthermore, we estimate the model using clustered standard errors at the village level (the primary sampling unit).

Table 7 shows the regression results for reading and math scores separately. In columns 1 and 3, we show the simple DD findings with no control variables, and in columns 2 and 4, we introduce the control variables[32]. Although the conflict in Kashmir in 2010 had a detrimental effect on reading scores, the effect is not statistically significant (See Table 7: columns 1 and 2). On the contrary, we find a negative and statistically significant effect on math performance. Math performance dropped by 0.18 standard deviations due to the civil conflict (See Table 7: columns 3 and 4). Since we do not account for the unobserved district, survey-year, and birth-year heterogeneity in our new identification strategy in the KPSM DD model, these results corroborate our main results (See Table A.5: columns 1 and 5). In Appendix Table A.9, we show that there the treated and control groups are similar on observable characteristics at the baseline, yet the treated group had higher reading scores to begin with.

Alternatively combining the coarsened exact matching method[33] with difference-in-differences (CEM DD) to also account for the unobservable heterogeneity, the results in

[31]See Villa (2016) for an overview.

[32]The treatment and the control groups are matched on the same control variables. Since we have access to most these variables throughout the study period, we include just these variables as controls. In order to increase the sample size, we also match the treated and the control groups on the individual characteristics like the child's age, gender and grade alone. The results are in congruence with our main findings in Table 2; we get negative and statistically significant effects in math and significant effects in reading only when we do not include the controls in regressions.

[33]For details, see Blackwell et al. (2009)

Table 7: *Effect of Violence on Student Performance in Reading and Math Tests: The Kernel Propensity Score Matching Difference-in-Differences (KPSM DD) to check for Selection into Violence*

	Standardized Reading Score		Standardized Math Score	
	(1)	(2)	(3)	(4)
Post	0.34***	0.36***	0.36***	0.39***
	(0.08)	(0.06)	(0.07)	(0.06)
Kashmir	0.16*	0.14**	0.13	0.12*
	(0.08)	(0.06)	(0.09)	(0.07)
Kashmir × *Post*	-0.10	-0.10	-0.18*	-0.18**
	(0.09)	(0.07)	(0.10)	(0.08)
Constant	-0.07	-2.35***	-0.02	-2.35***
	(0.07)	(0.10)	(0.06)	(0.11)
Controls	No	Yes	No	Yes
Observations	5,901	5,901	5,861	5,861
R-Squared	0.03	0.45	0.02	0.44

Note: See Table 2 Notes. Regressions are weighted using the kernel weights from the kernel propensity score matching and estimated on the common support of the propensity scores. Controls include the age, gender, grade and parental education of the student. Robust standard errors clustered at the village in parentheses. Data Sources: ASER Household Surveys from 2007-2012. Data for 2010 is not available. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A.10 are in line with our main findings. We find negative and statistically significant effect of conflict on the student performance in both the reading and math exams.

Given the ordinal nature of our test score variables, we used the standardized test scores as dependent variables in our analysis to avoid any measurement errors. However, we also separately estimate the linear probability models on each reading and math skill. The results presented in Appendix Table A.11 reveal that the conflict significantly decreased the probability of being able to read and solve arithmetic problems at various levels of mastery. Thus, these results are qualitatively the same as our main results that show that conflict negatively impacted educational quality in Kashmir. In addition to using linear probability models, we also create a new test score variable, the sum of the reading and math scores, to generate more variability in total test score, and then we standardized[34] it such that the mean is **0** and the standard deviation is **1**. Appendix Table A.12 shows the treatment effects with this new dependent variable. The DD point estimates are negative and statistically significant in all four models with various control variables. Thus, these results lend further support to our main results in Table 2.

7 Discussion and Conclusion

In Kashmir, a conflict-affected region where education is frequently disrupted, a median of 24 working days per year were lost between 2010 and 2017 (Parvaiz, 2017). The empirical research on school absenteeism and teacher strikes reveals that missing 10 days in grade 3 results in a 0.025SD reduction in math test scores, but missing the same 10 days in grade 5 resulted in a 0.088SD decline in arithmetic test scores (Aucejo & Romano, 2016). Based on this evidence, the consequences of conflict on educational quality in Kashmir could be substantial, yet there is no evidence of conflict-induced school closures in Kashmir. This study tries to fill this important gap and contributes to the existing literature by demonstrating the severity of violence's impact on schoolchildren and how it contributes to educational disparities.

This paper provides evidence that the 2010 unrest-induced school shutdowns in Kashmir adversely affected student performance on a nation standardized test. We find a largely negative and statistically significant effect on math performance (-0.22 standard deviations) and reading performance (-0.13 standard deviations). When accounting for individual, family, and village level covariates, the point estimates from the DD estimation slightly increase in magnitude and remain statistically significant. These negative effects do not fade two years post the unrest and are large in magnitude when compared with other relevant studies in the literature. The violence might have had a larger and more persistent effect on student test scores because of the existing dismal reading and math skills and also because students were exposed to the unrest for most of the academic year. We could not find any suggestive evidence of other possible channels like threat to one's life, direct bodily damage and psychological stress, etc. We also did not find any evidence of the probability of students dropping out of school in the post-conflict period, which might have affected their performance.

[34] We have standardized the test score by subtracting the mean of any given year and dividing by the standard deviation for the same year for each individual observation.

Our findings also indicate which groups are more vulnerable to conflicts. We find that girl and weaker students are most negatively affected by the conflict. We also find that the children in the middle and high schools are the worst impacted by the unrest, but we do not find any significant and economically meaningful negative effects for students in the upper tail of test score distributions (above median). If conflict primarily impacts low-performing children and does not harm those who are already doing well in school, it can have serious long-term effects in terms of increased educational inequalities, which are linked to income inequalities and differences in economic well-being (Hanushek & Woessmann, 2011; Rodríguez-Pose & Tselios, 2009). Numerous studies have demonstrated that the treatment effects of educational interventions on test score outcomes dissipate rapidly. According to Kane & Staiger (2008), Jacob et al. (2010) and Rothstein (2010), treatment effects fade by as much as 80% over the course of one year. In underdeveloped countries, more than 70 percent of an intervention's effect is lost within the first year after its termination (Banerjee et al., 2007). Therefore, learning loss, particularly during the formative years of childhood development, is largely irreparable. Regardless of the absence of a long-term effect of conflict on test scores, violence can harm a person's social skill set in the long run through deteriorating behaviours and future academic motivations as well as educational prospects of afflicted children (Michaelsen & Salardi, 2020).

Given the persistent nature of conflict and prevalence of curfews and shutdowns in Kashmir, the significance of our research lies in the fact that by assessing the impacts of the Kashmir conflict on student performance, policymakers may devise alternate teaching methods and provide safety nets for the most vulnerable. Our findings have significant policy implications. First, because any law-and-order issue in Kashmir is a natural occurrence, conflict-induced school closures are a shock to the learning process, especially if remote learning is not widely available. As a result, governments must ensure that schools operate uninterrupted and, more importantly, offer a safe atmosphere where parents can feel secure about their children. Second, authorities must ensure that the most vulnerable populations, such as the female and the weaker students, receive sufficient attention. Third, governments must ensure that every student has access to remote learning equipment, such as mobile phones and laptops, and oblige school administrators to continue lecturing through online mode in the event of future conflict events.

Although we show that the effect of violence persists and is strong, we could not document the long-term effects of conflict in Kashmir due to lack of access to panel data. Furthermore, because parental exposure to conflict may affect children's educational attainment and achievement, we are unable to document these inter-generational impacts.

As a result, future studies should focus on the long-term and inter-generational effects of the Kashmir conflict.

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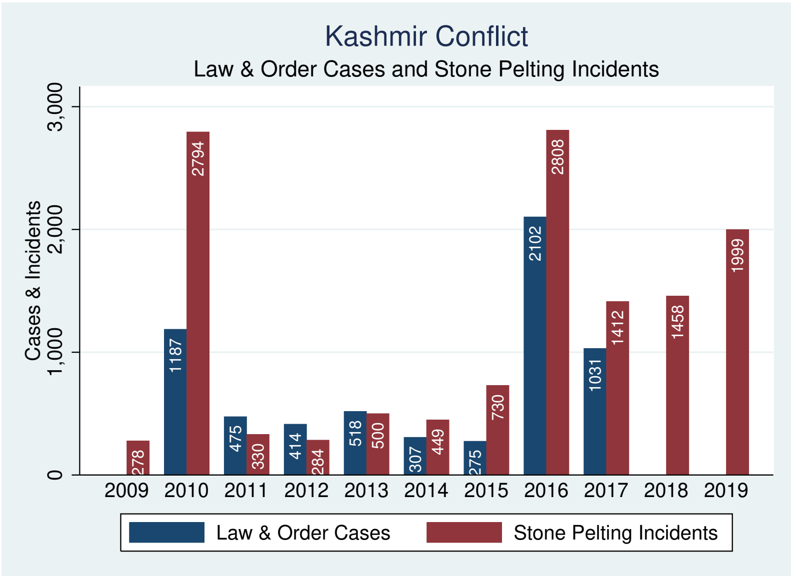
Appendix A

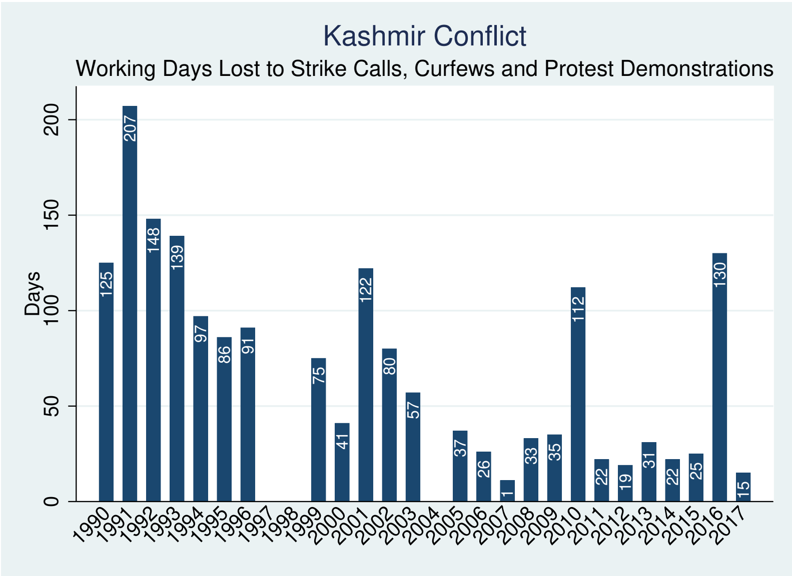
Appendix A Figures

Figure A.1: *Kashmir Conflict: Law & Order and Stone Pelting Incidents*



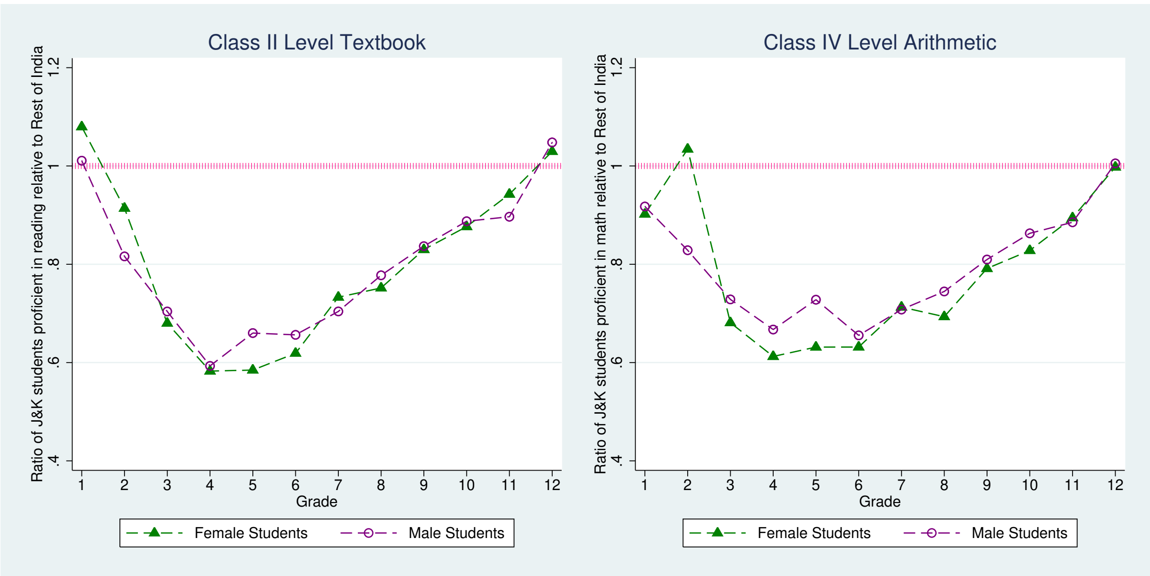
Note: Data Sources:- Law & Order Cases (Parvaiz, 2017); Stone Pelting Incidents (Ganie, 2021)

Figure A.2: *Kashmir Conflict: Number of Working Days Lost to Violence*



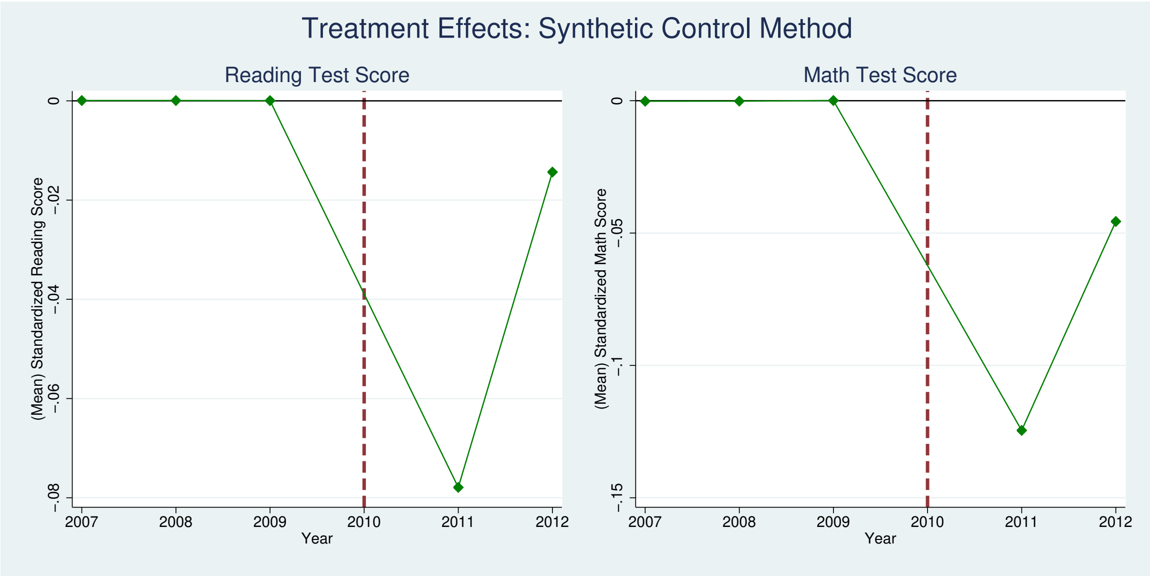
Note: Data Sources:- (Parvaiz, 2017)

Figure A.3: *Gender & Grade Wise Literacy and Numeracy of Students (in 1-12 grades) in Jammu and Kashmir relative to the Rest of India*



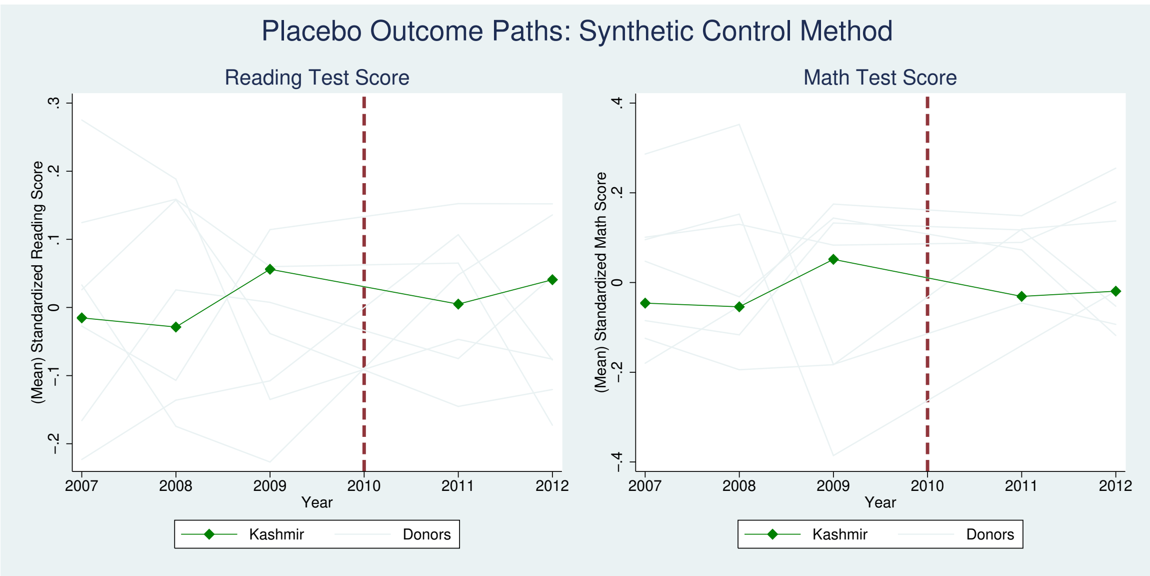
Note: Data Source: ASER Household Surveys from 2007-2012. Data for 2010 is not available.

Figure A.4: *Intent-to-Treat Effect of Violence on Student Achievements: Synthetic Control Method*



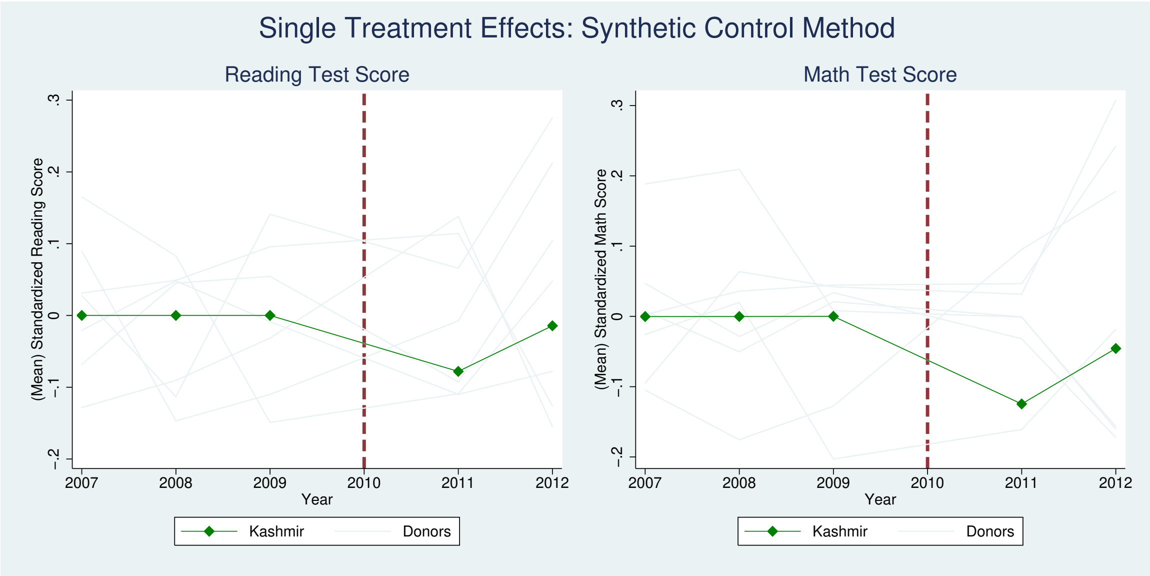
Note: Outcome variables are the standardized test scores on reading and math exams averaged over districts and years. The figure is generated in Stata using the command *synth_runner*. Data Source: ASER Household Surveys from 2007-2012. Data for 2010 is not available.2

Figure A.5: *Placebo Outcome Paths: Synthetic Control Method*



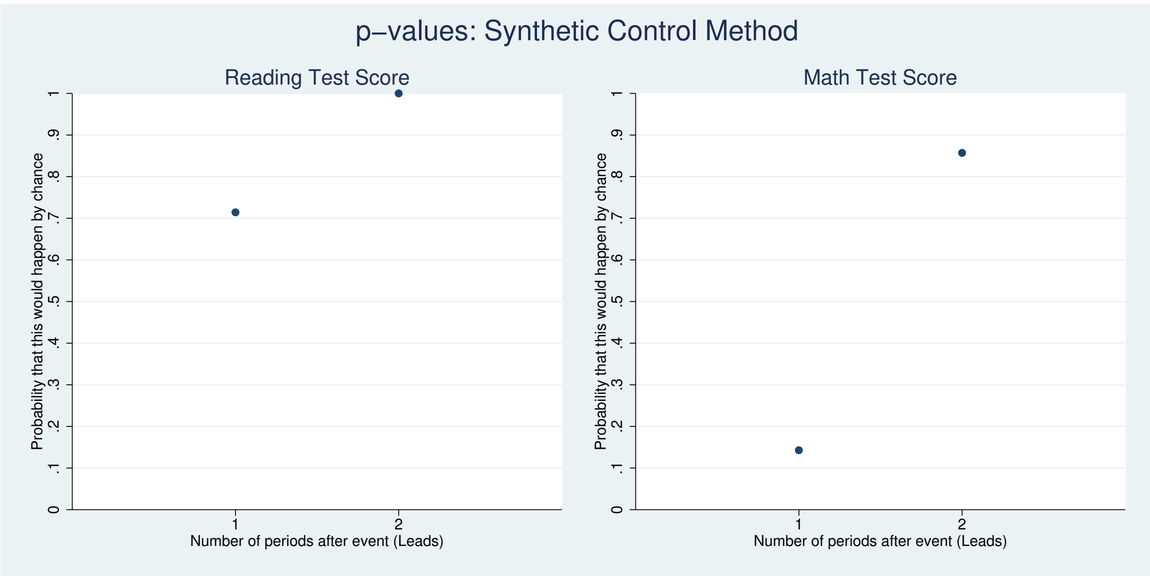
Note: See Figure A.4 Notes

Figure A.6: *Placebo Intent-to-Treat Effects: Synthetic Control Method*



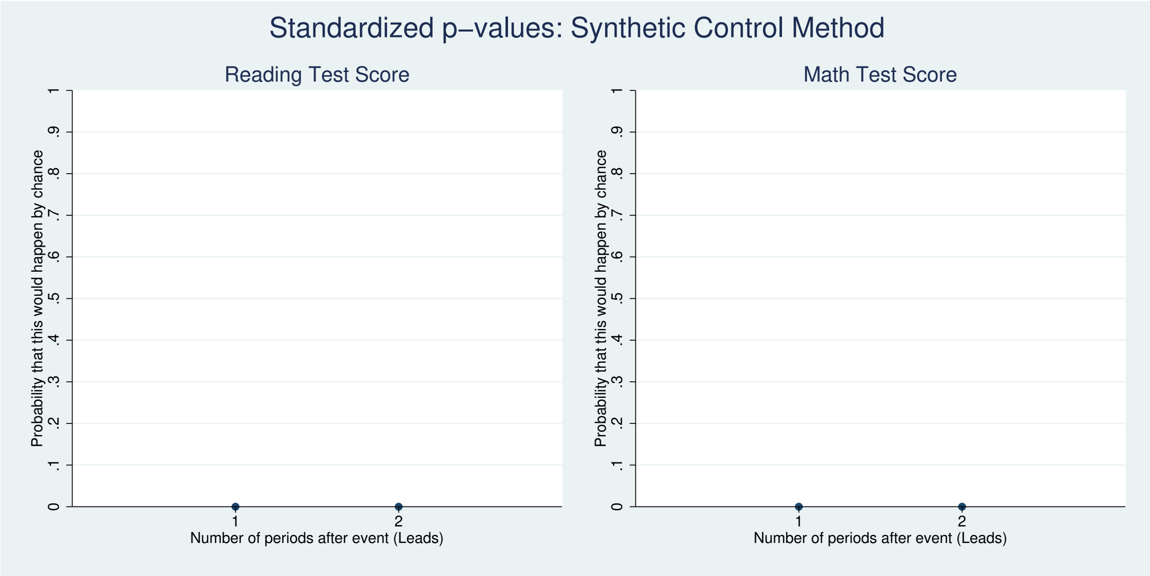
Note: See Figure A.4 Notes

Figure A.7: *p-values: Synthetic Control Method*



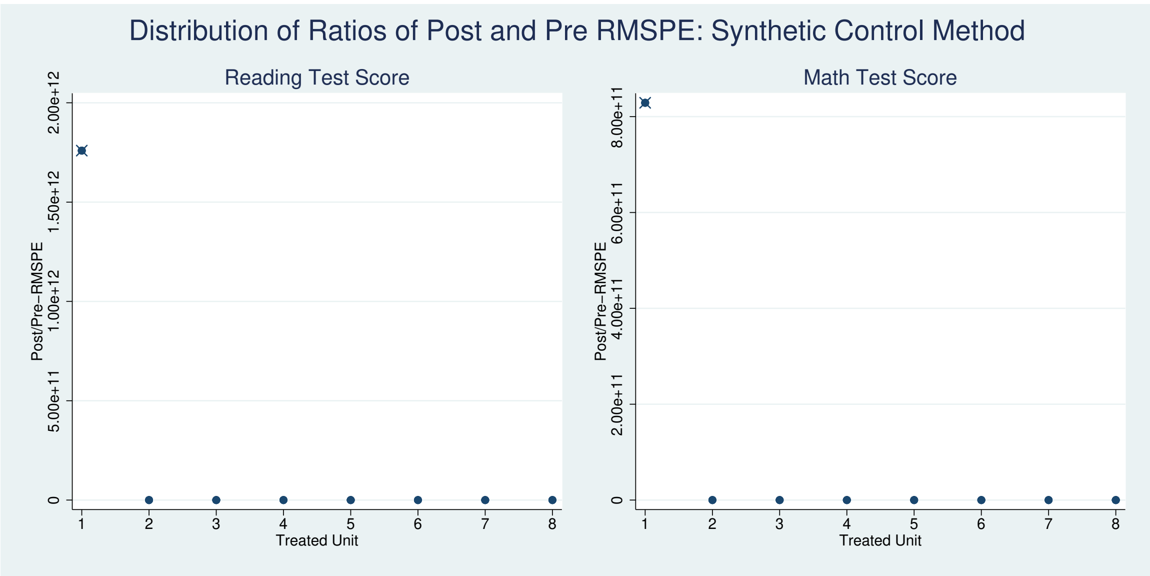
Note: The figure is generated in Stata using the command *synth_runner*. Data Source: ASER Household Surveys from 2007-2012. Data for 2010 is not available.

Figure A.8: *Standardized p-values: Synthetic Control Method*



Note: See Figure A.7 Notes.

Figure A.9: *Post and Pre RMSPE Ratios: Synthetic Control Method*



Note: Dependent variable is the ratio of post and pre 2010 unrest root mean square prediction errors. The figure is generated in Stata using the command *synth_runner*. Data Source: ASER Household Surveys from 2007-2012. Data for 2010 is not available.

Appendix A Tables

Table A.1: *Descriptive Statistics*

	Control Group		Treated Group	
	Pre-Unrest Mean (SD)	Post-Unrest Mean (SD)	Pre-Unrest Mean (SD)	Post-Unrest Mean (SD)
Individual Characteristics				
Age	9.69	9.88	10.29	10.35
	(3.81)	(3.70)	(3.61)	(3.69)
Gender (1=Male)	0.55	0.53	0.54	0.51
	(0.50)	(0.50)	(0.50)	(0.50)
Grade	5.19	5.35	5.52	5.57
	(2.99)	(2.96)	(3.08)	(3.01)
Household Characteristics				
Mother's Age	35.32	35.19	35.35	35.28
	(6.90)	(7.15)	(5.84)	(7.27)
Father's Age	39.28	40.11	39.07	39.46
	(7.50)	(8.00)	(5.68)	(7.92)
Mother's Education (Grades Completed)	8.75	8.81	7.50	8.69
	(2.94)	(2.97)	(3.17)	(3.12)
Father's Education (Grades Completed)	9.95	9.43	10.69	9.78
	(2.95)	(2.73)	(2.79)	(3.20)
HH Electricity (1=Yes)	0.87	0.70	0.72	0.63
	(0.34)	(0.46)	(0.45)	(0.48)
HH Mobile (1=Yes)	0.65	0.76	0.73	0.87
	(0.48)	(0.43)	(0.45)	(0.34)
HH Size	6.94	7.29	7.79	7.73
	(3.06)	(3.67)	(3.23)	(3.07)
Pucca House (1=Yes)	0.30	0.40	0.36	0.51
	(0.46)	(0.49)	(0.48)	(0.50)
Village Characteristics				
Village Electricity (1=Yes)	0.97	0.96	0.95	0.97
	(0.18)	(0.19)	(0.22)	(0.17)
Village Pucca Road (1=Yes)	0.74	0.59	0.64	0.69
	(0.44)	(0.49)	(0.48)	(0.46)
Village Ration Shop (1=Yes)	0.67	0.65	0.82	0.83
	(0.47)	(0.48)	(0.38)	(0.38)

Note: Treated group comprises the districts of Kashmir valley while control group comprises the districts of Rajauri, Jammu, Leh(Ladakh) and Kargil districts of Jammu and Ladakh regions. Pre and Post-unrest are the periods before and after 2010 unrest. Data Source: ASER Household Surveys from 2007-2012. Data for 2010 is not available.

Table A.2: *Control Weights: Synthetic Control Method*

	Reading	Math
Control District	Control Weight	Control Weight
Doda	0.034	0.042
Jammu	0.024	0.141
Kargil	0.146	0.133
Kathua	0.110	0.082
Leh(Ladakh)	0.566	0.136
Punch	0.068	0.051
Rajauri	0.052	0.415

Note: These weights are obtained by the Synthetic Control Method in Stata using the *synth* command. Data Source: ASER Household Surveys from 2007-2012. Data for 2010 is not available.

Table A.3: *Predictor Balance: Synthetic Control Method*

	Reading		Math	
Variable	Treated	Synthetic	Treated	Synthetic
Child Age	10.305	9.860	10.305	9.727
Child Gender (1=Male)	0.542	0.531	0.542	0.561
Grade	5.504	5.240	5.504	5.235
Mother's Education	7.530	8.356	7.530	8.503
Std. Test Score (2007)	-0.015	-0.015	-0.046	-0.046
Std. Test Score (2008)	-0.029	-0.029	-0.054	-0.054
Std. Test Score (2009)	0.056	0.056	0.052	0.052

Note: See Table A.2 Notes. Std. Score refers to the standardized test score for all the pre-unrest years which are taken as the predictor variables to construct the synthetic version of the treated districts of Kashmir.

Table A.4: *Intent-to-Treat Effects: Synthetic Control Method*

	Standardized Reading Score			Standardized Math Score		
	ITT Effect	p-value	Standardized p-value	ITT Effect	p-value	Standardized p-value
2011	-0.078	0.714	0	-0.125	0.143	0
2012	-0.014	1	0	-0.046	0.857	0

Note: Outcome variables reading score and math score are standardized by year such that the mean and standard deviation for each year is 0 and 1, respectively. We have averaged out the standardized test score at the district level for each year to construct a pseudo panel at the district. These treatment effects are obtained by the Synthetic Control Method in Stata using the *synth_runner* command. p-value lists the percentage of placebo effects that are as large as the main effect. The standardized p-value represents the percentage of standardized effects that are at least as large as the main standardized effect. In other words, this standardized measure takes the quality of pre-treatment match into account as opposed to the p-value. For further details, see Galiani & Quistorff (2017). Data Source: ASER Household Surveys from 2007-2012. Data for 2010 is not available.

Table A.5: *Effect of conflict on the student performance: Intent-to-Treat Effects with varied sets of Fixed Effects*

	Standardized Reading Score				Standardized Math Score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Kashmir	0.09				0.07			
	(0.07)				(0.07)			
Post	0.34***	0.39***			0.35***	0.40***		
	(0.06)	(0.06)			(0.07)	(0.07)		
Kashmir × *Post*	-0.07	-0.14*	-0.14*	-0.13*	-0.16*	-0.23***	-0.23***	-0.22***
	(0.08)	(0.08)	(0.08)	(0.07)	(0.09)	(0.09)	(0.09)	(0.08)
Constant	-2.73***	-2.64***	-2.61***	-1.06***	-2.66***	-2.66***	-2.64***	-1.24***
	(0.20)	(0.21)	(0.20)	(0.24)	(0.19)	(0.19)	(0.19)	(0.21)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,547	5,547	5,547	5,547	5,506	5,506	5,506	5,506
R-Squared	0.46	0.47	0.47	0.49	0.44	0.46	0.46	0.48
District FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Birth-Year FE	No	No	No	Yes	No	No	No	Yes

Note: See Table 2 Notes. Robust standard errors clustered at the village in parentheses. Data Sources: ASER Household Surveys from 2007-2012. Data for 2010 is not available. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: *Effect of Conflict on Drop-Out Rates*

	Out of School: Drop-Out					
	(1)	(2)	(3)	(4)	(5)	(6)
Kashmir	-0.17**	-0.15*				
	(0.09)	(0.09)				
Post	0.13	0.15	0.25**			
	(0.09)	(0.09)	(0.10)			
$Kashmir \times Post$	0.01	-0.00	-0.09	-0.01	-0.02	-0.03
	(0.11)	(0.11)	(0.11)	(0.08)	(0.08)	(0.08)
$Kashmir \times Post \times Male$						0.04
						(0.06)
Constant	0.55***	1.06***	0.94***	1.07***	0.97***	0.97***
	(0.08)	(0.16)	(0.15)	(0.08)	(0.02)	(0.02)
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	1,078	1,054	1,054	1,054	1,054	1,054
R-Squared	0.03	0.05	0.08	0.54	0.54	0.54
District FE	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes
Birth-Year FE	No	No	No	No	Yes	Yes

Note: See Table 2 Notes. Outcome variable *drop-out* is a dummy variable taking value **1** for those students who dropped out of school after 2010 and **0** for those who dropped before 2010. The estimated model is a linear probability model. Controls include the age and gender of the child. Robust standard errors clustered at the village in parentheses. Data Sources: ASER Household Surveys from 2007-2012. Data for 2010 is not available. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: *Treatment Placebo Test: Check for Spillover Effects of Violence*

	Standardized Reading Score				Standardized Math Score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Jammu	-0.09				-0.05			
	(0.08)				(0.08)			
Post	0.34***	0.37***			0.31***	0.33***		
	(0.08)	(0.08)			(0.07)	(0.08)		
Jammu $\times$ *Post*	0.05	0.02	0.02	0.00	0.07	0.05	0.05	0.04
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Constant	-2.68***	-2.80***	-2.81***	-0.46*	-2.65***	-2.71***	-2.72***	-0.44
	(0.18)	(0.17)	(0.17)	(0.27)	(0.19)	(0.18)	(0.18)	(0.28)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,252	3,252	3,252	3,252	3,230	3,230	3,230	3,230
R-Squared	0.45	0.45	0.45	0.46	0.44	0.44	0.44	0.46
District FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Birth-Year FE	No	No	No	Yes	No	No	No	Yes

Note: See Table 2 Notes. *Jammu* is a pseudo treatment dummy taking value **1** for districts Jammu, Doda and Kathua in in Jammu region of J&K and **0** for districts Leh and Ladakh in Ladakh region. Robust standard errors clustered at the village in parentheses. Data Sources: ASER Household Surveys from 2007-2012. Data for 2010 is not available. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: *Effects of Conflict with District-Specific Linear Time Trends and District-Birth Year Fixed Effects*

	Standardized Reading Score				Standardized Math Score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Kashmir × *Post*	-0.09**	-0.10**	-0.52***	-0.55***	-0.14***	-0.17***	-0.37***	-0.40***
	(0.04)	(0.05)	(0.11)	(0.11)	(0.04)	(0.05)	(0.12)	(0.12)
Constant	0.90***	0.90***	88.05**	118.54**	0.81***	0.74***	67.69	92.55*
	(0.06)	(0.12)	(44.05)	(47.77)	(0.07)	(0.16)	(47.49)	(52.74)
Observations	46,621	46,621	46,621	46,621	46,267	46,267	46,267	46,267
R-Squared	0.45	0.46	0.46	0.46	0.42	0.43	0.43	0.43
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District x Birth-Year	No	Yes	No	Yes	No	Yes	No	Yes
District Specific Trend	No	No	Yes	Yes	No	No	Yes	Yes

Note: See Table 2 Notes. We do not control for any background information so as to increase sample size because we lose significant number of observations as depicted in Table 2. Robust standard errors clustered at the village in parentheses. Data Sources: ASER Household Surveys from 2007-2012. Data for 2010 is not available. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: *Baseline Balance Test: KPSM DD*

Weighted Variables	Mean Control	Mean Treated	Difference
Panel A: Standardized Reading Score			
Test Score	-0.068	0.088	0.156*
Child's Age	10.750	10.831	0.082
Child's Gender (1=Male)	0.610	0.622	0.012
Child's Grade	5.221	5.276	0.055
Mother's Education	8.630	8.552	-0.078
Father's Education	11.338	11.504	0.166
Observations	10325	19910	30235
Panel A: Standardized Math Score			
Test Score	-0.024	0.108	0.133
Child's Age	10.760	10.840	0.079
Child's Gender (1=Male)	0.611	0.623	0.012
Child's Grade	5.242	5.291	0.049
Mother's Education	8.633	8.541	-0.093
Father's Education	11.332	11.491	0.158
Observations	10180	19753	29933

Note: Outcome variables reading score and math score are standardized by year such that the mean and standard deviation for each year is 0 and 1, respectively. Variables are weighted by the kernel weights from the kernel propensity score matching. Means and t-tests are estimated by linear regression on common support of the propensity scores. t-tests are carried out at the baseline in the absence of unrest (i.e. 2007-2009). Robust standard errors clustered at village in parentheses. Data Sources: ASER Houehold Surveys from 2007-2012. Data for 2010 is not available. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: *The Endogeneity Concern: Estimating the Effect of Conflict using the Coarsened Exact Matching Difference-in-Differences (CEM DD)*

	Standardized Reading Score			Standardized Math Score		
	(1)	(2)	(3)	(4)	(5)	(6)
Kashmir × *Post*	-0.07*	-0.08*	-0.45***	-0.11**	-0.14***	-0.33***
	(0.04)	(0.05)	(0.11)	(0.04)	(0.05)	(0.12)
Constant	0.92***	0.90***	88.96**	0.83***	0.74***	68.51
	(0.06)	(0.12)	(44.07)	(0.06)	(0.16)	(47.51)
Observations	46,606	46,606	46,606	46,251	46,251	46,251
R-Squared	0.45	0.46	0.46	0.42	0.43	0.43
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District-Birth-Year FE	No	Yes	No	No	Yes	No
District-Specific Linear Trend	No	No	Yes	No	No	Yes

Note: See Table 2 Notes. The control and treated groups are matched on the individual characteristics, age, gender and grade. The regressions are weighted using the CEM weights. Data Source: ASER Household Surveys from 2007-2012. Data for 2010 is not available. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.11: *The Effect of Conflict on the Probability of Reading and Solving Math Problems at Various Assessment Levels*

	Reading Assessment Levels				Math Assessment Levels			
	Letters	Words	Paragraph	Story	Digits 1-9	Digits 10-99	Subtraction	Division
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Kashmir × *Post*	-0.11***	-0.11***	-0.08***	-0.04**	-0.11***	-0.10***	-0.09***	-0.07***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	0.94***	0.92***	0.86***	0.78***	0.91***	0.87***	0.85***	0.75***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
Observations	55,364	55,364	55,364	55,364	55,364	55,364	55,364	55,364
R-Squared	0.30	0.36	0.38	0.32	0.28	0.33	0.36	0.28
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: See Table 2 Notes. Each of the dependent variables is a dummy taking value **1** if the highest level at which the child can read and do math is given by the model labels and **0** otherwise. The estimated models are the linear probability models. Data Source: ASER Household Surveys from 2007-2012. Data for 2010 is not available. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.12: *Intent-to-Treat Effects with Total Test Score as Dependent Variable*

	Standardized Test Score			
	(1)	(2)	(3)	(4)
Kashmir × *Post*	-0.12***	-0.09**	-0.18**	-0.17**
	(0.04)	(0.05)	(0.08)	(0.08)
Constant	0.92***	0.15	-0.94***	-1.23***
	(0.06)	(0.14)	(0.14)	(0.23)
Individual Controls	No	Yes	Yes	Yes
Household Controls	No	No	Yes	Yes
Village Controls	No	No	No	Yes
Observations	46,097	40,365	5,627	5,493
R-Squared	0.49	0.46	0.53	0.54
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes

Note: See Table 2 Notes. Outcome variable test score, which is the summation of reading and math scores, is standardized by year such that the mean and standard deviation for each year is 0 and 1, respectively. Data Source: ASER Household Surveys from 2007-2012. Data for 2010 is not available. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$