Civil unrest and learning outcomes in India*

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Abstract

In this paper, we quantify the impact of civil unrest on the learning outcomes of school-aged children in Kashmir, India. Using a difference-in-differences design and exploiting a plausibly exogenous shock to the intensity of violence in the summer of 2010, we show that students exposed to the unrest perform significantly worse on language and math tests. The negative effects persist for at least two years and are larger for middle school students. We do not find differential effects by gender, socioeconomic status, and school type. Additional results reveal that civil unrest has no impact on the probability of dropping out of school, but we find some evidence of reduced school enrolment. We provide suggestive evidence of reduced school quality and increased psychological stress as plausible underlying mechanisms linking civil unrest to the deterioration of learning outcomes. The results are robust to alternative specifications, test-score measurements, selection into violence and violation of parallel trends.

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Keywords: Learning outcomes, Education, Conflict, Civil unrest, Kashmir, DID

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1 Introduction

Civil conflicts affect about half the countries in the world (Blattman & Miguel, 2010). They have been widespread post the World War II period (León, 2012) and persistent in nature (Blattman & Miguel, 2010). These conflicts are particularly common in less developed countries (Brown & Velásquez, 2017) where most conflicts in the later half of the twentieth century took place (León, 2012). For instance, civil conflict has broken out in nearly two-thirds of sub-Saharan African nations since 1980 (Bellows & Miguel, 2009). An extensive literature documents that civil wars as well as civil conflicts[1] affect children's human capital formation, notably nutrition in early childhood (Bundervoet et al., 2009; Akresh et al., 2012a,b; Mansour & Rees, 2012; Minoiu & Shemyakina, 2014; Akbulut-Yuksel, 2014; Weldeegzie, 2017)[2] and education in school-going years (Ichino & Winter-Ebmer, 2004; Akresh, 2008; Blattman & Annan, 2010; Chamarbagwala & Morán, 2011; Merrouche, 2011; Parlow, 2011; Poirier, 2012; Alfano & Görlach, 2022; Guo, 2020; Dabalen & Paul, 2014)[3]. However, relatively little is known about the effect of low-intensity conflicts such as *"civil unrest"*, which may stubbornly persist and disrupt civilian life — via the law and order issues, school closures and non-functioning of the institutions of governance — and can lead to fear, uncertainty, insecurity and anxiety among population.

In this paper, we investigate the effects of civil conflict by examining how exposure to civil unrest during school age affect educational quality as measured by student performance on basic literacy and numeracy tests. We focus on Kashmir, a locale that has been exposed to a persistent low-intensity civil conflict over a period of at least 35 years. Although the Kashmir conflict originated as an armed confrontation in 1989, it has predominantly manifested as a civil conflict since 2010 (Parvaiz, 2017). In May 2010, Indian soldiers, mistakenly perceiving three individuals as terrorists infiltrating from Pakistan, tragically killed them. However, the tragedy sparked widespread uproar when a rare police investigation revealed that those killed were innocent civilians (Bukhari, 2010). Consequently, the summer of 2010 witnessed a highly violent conflict in Kashmir, leading to the loss of 112 lives — the majority of casualties were students (40%) and young adults in their twenties (80%), spread across all districts of Kashmir, with one incident occurring in the Poonch district of the Jammu region (Dar, 2010). The deaths of civilians created safety concerns and put lives in danger throughout the Kashmir valley, which was under a round-the-clock curfew (Bukhari, 2010) and schools remained shut for nearly 4 months[4]. Within this environment of uncertainty, fear and insecurity, it is reasonable to anticipate that the negative effects of violence will extend beyond the harm directly caused by the conflict — in terms of loss of life and property — and have severe indirect effects on student test scores. This anticipation arises because violent conflicts could potentially disrupt school calendars, elevate rates of absenteeism among both instructors and students and may lead to significant psychological suffering (Monteiro & Rocha, 2017).

Our identification strategy exploits a sudden and plausibly exogenous spike in violence in 2010 in the Indian administrated part of Jammu and Kashmir. The ongoing Kashmir conflict gives us an excellent setting to quantify the effect of violence on educational outcomes because of its peculiarity. The conflict is predominantly concentrated in the Muslim majority region of the state, the Kashmir valley, while the other two regions of the state, namely, Jammu and Ladakh populated largely by Hindus and Buddhists respectively were unaffected by the violence. This setting provides us a natural experiment and allows us to quantify the causal effects of conflict

[1] Civil wars — experienced by approximately one-third of all nations — are internal conflicts resulting in an annual death toll of 1,000 battle deaths or more, while civil conflicts —– internal conflicts that affect at least half of the world's countries — have an annual death toll of 25 or more battle deaths (Blattman & Miguel, 2010).

[2] Besides nutrition in the early childhood, the literature has also documented long-term negative effects of early life exposure to war on mental health in the adulthood (Singhal, 2019).

[3] Exposure to conflicts can also have gender differential effects on schooling depending upon the context of the conflict. For a brief discussion, see Buvinić et al. (2014). In addition, in some contexts such as Nepal, conflict can have no effect on school attainment (Pivovarova & Swee, 2015) or it can have a positive effect (Valente, 2014).

[4] https://www.indiatoday.in/india/story/schools-reopen-in-kashmir-valley-after-4-months-82724-2010-09-26

using the difference-in-differences (DID) design, where Kashmir is treated and Jammu and Ladakh are not treated. The identification under the difference-in-differences design crucially hinges on "parallel trends" assumption, which in our case means that, absent the 2010 mass unrest, the test scores of students in the treated Kashmir and untreated Jammu and Ladakh would evolve in parallel to each other. However, districts impacted and not impacted by the conflict may be systematically different from one another and this may cause the parallel trends assumption to not hold. In fact, it does not hold when we use all the districts in Jammu and Ladakh regions as comparison group. Therefore, we use only a subset of all the districts in Jammu and Ladakh as a counterfactual group for which the parallel trends assumption holds[5]. As a robustness check, we present results with all the districts as the comparison group and check the sensitivity of the causal estimates to the violation of parallel trends by following Rambachan & Roth (2023).

Using the data on student test scores from the Annual Status of Education Report (ASER) Surveys from 2007-2012[6], we find significant negative effect of civil unrest on language and math test scores. The exposure to the violence reduces the reading test score by 0.543 standard deviations and the math test score by 0.369 standard deviations. We show that these negative effects of violence do not fade until at least two academic years after the unrest is over. These results are robust to the inclusion (exclusion) of time fixed effects, district-specific linear time trends and a bunch of control variables. Further, they are also robust to a number of checks ranging from alternative specifications, alternative identification, test score measurements and selection into violence issues. Besides, our causal estimates are also robust the violation of parallel trends. We do not find any differential effects by gender of the child, the type of dwelling the child resides in and the type of school the child attends. However, the detrimental effects are more pronounced for students in grades 6-8.

Additional results reveal that the exposure to civil unrest has large negative and statistically significant effects for students who lie in the lower tail (up to the median) of the test score distributions and has no economically meaningful and statistically significant effects for students who lie in the upper tail (above median) of the test score distributions. Coupled with the persistence of these effects, this result has serious implications for future inequalities between the two sets of students. Conflict may have a negative impact on a child's future educational trajectory and contribute to the perpetuation of existing inequities if exposure to violence disproportionately affects students with lower academic performance while children with higher performance are unaffected. Further, we find that violent conflict of 2010 has no effect of the probability of dropping out of school but we do find some evidence of reduced school enrolment.

Turning to the mechanisms, violent conflicts can affect children's learning outcomes via a number of channels. First, conflict could affect student test scores via the supply side factors such as school closures, teacher absenteeism, damage to school infrastructure and deterioration in quality of schooling (Akbulut-Yuksel, 2014; Monteiro & Rocha, 2017; Brück et al., 2019; Kibris, 2015). Second, they could also affect student learning via the demand side factors such as student absenteeism, tardiness and parental distress (Jarillo et al., 2016). The third and more important channel which can explain how conflict can impact student learning is the psychological stress among students (Brück et al., 2019; Michaelsen & Salardi, 2020; Ang, 2020). We investigate the role of each of these channels and find that the loss of instructional time due to factors such as school closures or student absenteeism do not plausibly explain our findings. Rather, we find that in addition to the quality of schooling, increased psychological stress due to a general sense of fear and insecurity may be important mechanisms which can explain these large and persistent negative effects of conflict on student learning outcomes.

We contribute to the growing literature on the educational consequence of exposure to wars,

[5]We proceed by checking if the parallel trends assumption holds for each district separately and then combine a set of districts for which the assumption holds true. More on this in Section 4

[6]The data for the year 2010 is not available for the state of Jammu and Kashmir.

violent conflicts, crime and other forms of violence (for review, see Justino (2011); Verwimp et al. (2019).). An extensive literature has documented that exposure to conflicts reduces the years of education completed (Akresh, 2008; Shemyakina, 2011; Chamarbagwala & Morán, 2011; Merrouche, 2011; León, 2012; Dabalen & Paul, 2014; Verwimp & Van Bavel, 2014; Diwakar, 2015; Swee, 2015; Islam et al., 2016; Bharati, 2022; Singh & Shemyakina, 2016; Bertoni et al., 2019; Weldeegzie, 2017; Brown & Velásquez, 2017), reduces enrolment (Bertoni et al., 2019; Weldeegzie, 2017; Shemyakina, 2011; Roy & Singh, 2016), increases the dropout rates (Koppensteiner & Menezes, 2021; Brown & Velásquez, 2017; rodríguez & sánchez, 2012) and reduces school attendance (Koppensteiner & Menezes, 2021; Brown & Velásquez, 2017; Di Maio & Nandi, 2013; Justino et al., 2014). The negative effects of violent conflicts on the quantity of education have been extensively studied in terms of educational attainment, school enrollment, and school dropout rates; however, the negative effects of violence on the quality of education, as measured by student performance on various exams, have been studied much less. The existing literature has studied the effects of drug-related violence on test scores in Mexico (Michaelsen & Salardi, 2020; Jarillo et al., 2016), and Brazil (Monteiro & Rocha, 2017), police violence (Ang, 2020) and sniper attacks (Gershenson & Tekin, 2018) in United States, mass shooting in Norway (Bharadwaj et al., 2021), homicides in Brazil (Koppensteiner & Menezes, 2021), war in Ethiopia (Weldeegzie, 2017), terror attacks in Israel (Shany, 2023) and civil conflicts in Palestine and Turkey (Brück et al., 2019; Jürges et al., 2022; Kibris, 2015).

We make at least three important contributions to the literature on the microeconomic effects of conflicts on educational quality. Firstly, this paper redirects the focus from violence associated with drugs, police shootings, sniper attacks, homicides, and wars to civil unrest. By examining the indirect effects of exposure to conflict-induced curfews and shutdowns on student test scores, which to the best of our knowledge, have not been previously explored in the literature, this study sheds light on a previously neglected aspect. Instead of directly assessing the impact of violence exposure, this paper more plausibly captures the effects of fear and insecurity on educational quality. Existing studies have primarily investigated the direct effects of violence exposure and have found localized negative effects of drug violence on student achievements in Brazil (Monteiro & Rocha, 2017) and Mexico (Michaelsen & Salardi, 2020), police violence (Ang, 2020), and sniper attacks (Gershenson & Tekin, 2018) in the United States and mass shooting in Norway (Bharadwaj et al., 2021)[7]. These studies indicate that the detrimental effects diminish significantly as the distance from the attack site increases. In a recent study, Shany (2023) found that exposure to terror attacks in Israel has a negative but temporary (indirect) effect on exam performance that increases with the number of casualties and diminishes with the student's distance from the attack site. In contrast, our findings document widespread and persistent negative (indirect) effects on student performance, extending for at least two academic years following the occurrence of civil unrest.

Our second contribution to the literature lies in providing, what we believe to the best of our knowledge, the first causal evidence of how exposure to civil unrest specifically affects children's fundamental literacy and numeracy skills in grades 1-12. While previous studies have examined the effects of various forms of violence on grade-appropriate test scores such as GPA (Ang, 2020; Bharadwaj et al., 2021), high school exams (Brück et al., 2019; Shany, 2023), or grade-appropriate standardized tests (Michaelsen & Salardi, 2020; Monteiro & Rocha, 2017; Gershenson & Tekin, 2018; Koppensteiner & Menezes, 2021), our research is distinct in its focus on determining the impact of civil conflicts on the ability of exposed cohorts to read basic grade two level text and solve elementary arithmetic problems at grade three and four levels. By investigating this specific aspect of educational competence, our findings contribute significantly to understanding the educational ramifications of civil unrest.

Lastly, our study contributes by shifting away from examining the average effects of conflicts

[7] Bharadwaj et al. (2021) find that, in the short-run, children who survive the mass shooting have lower GPA (about 0.5 standard deviations) and in the long-run they have fewer completed years of schooling.

and instead focuses on the distributional consequences of violence exposure. To the best of our knowledge, only one prior study (Brück et al. (2019)) has attempted to explore these distributional consequences by utilizing quantile regressions. We also report results from the quantile regressions along the entire test score distributions. This approach deepens our understanding of the distributional effects of violence exposure, which in turn has significant long-term implications for income inequalities. By examining how violence affects different groups of the student population, our study provides valuable insights into the heterogenous impact of conflicts on educational outcomes and subsequent socioeconomic disparities.

The rest of this paper is organized as follows. In the following section, we provide a brief background on Kashmir conflict and the education system of Kashmir. Section 3 describes data and descriptive statistics. We discuss the empirical strategy and identification in section 4. Section 5 presents the main results, while section 6 discusses few important underlying mechanisms. We present a battery of robustness checks in section 7 before we conclude the paper in section 8.

2 Background

2.1 The Kashmir Conflict

Jammu and Kashmir, the nucleus of a long-standing territorial dispute between India and Pakistan, is the northernmost state among the 29 states of India[8]. The state is comprised of three major regions: Jammu, Kashmir — also known as the Valley, and Ladakh (see Figure 1a for details). The Kashmir valley is largely populated by Muslims, while Jammu is a Hindu majority, and Ladakh is a Buddhist majority region. The history of modern-day Jammu & Kashmir dates to 1846, when the Hindu Dogra ruler, Gulab Singh, purchased Kashmir from the British (Schofield, 2021). It was a princely state till the partition of British India in 1947, which led to the creation of two independent nations, India and Pakistan. The India-Pakistan partition of 1947 compelled Maharaja Hari Singh — the great-grandson of Gulab Singh — to make a critical decision between staying independent or affiliating with either India or the newly formed state of Pakistan, leading to an initial period of indecision followed by his eventual accession to India after nearly two months of delay[9] (Schofield, 2021).

[Figure 1 about here]

This resulted in a full-scale war between India and Pakistan in 1947-1948, with both countries sending troops to Kashmir (Ganguly, 2002). The United Nations intervened, and a ceasefire was eventually brokered. The ceasefire line, known as the Line of Control (LoC), divided the region into two parts: one administered by India, known as Jammu and Kashmir, and the other administered by Pakistan, known as Azad Kashmir and Gilgit-Baltistan. Since then, the dispute has remained unresolved, and Kashmir has become a heavily militarized zone. The dispute is characterized by intermittent outbreaks of violence, cross-border skirmishes, and periodic uprisings by the separatist groups. Both India and Pakistan have fought multiple wars over Kashmir, in 1965, 1971 and 1999, further exacerbating the tensions between them (Ganguly, 2002).

The roots of the Kashmir conflict can be traced back to 1989 when the Muslim residents of the Kashmir valley of J&K initiated an independence movement, expressing their dissatisfaction with India (Schofield, 2021). Some of these wanted to join Pakistan, while others wanted complete independence for their princely state. Nonetheless, the rest of Jammu's population, which is Hindu and Sikh, and Buddhist in Ladakh, never supported the movement (Ganguly,

[8] 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

[9] This eventual accession was a result of a rebellion that broke out in Poonch district of Kashmir in which tribesmen from Pakistan moved into Kashmir territory (Ganguly, 2002)

2002). The conflict intensified through the 1990s, when bombings, grenade explosions, and cross-firing were the norm (Parvaiz, 2017). Appendix Figure A.4 shows the number of insurgency related incidents and associated fatalities.

[Figure 2 about here]

Although the initial conflict in Kashmir emerged as an armed confrontation in 1989, it has predominantly taken the form of a civil unrest since 2010 (Parvaiz, 2017). The summer of 2010 marked an extraordinary period of violence in the State of Jammu and Kashmir, characterized by widespread violent protests and demonstrations within the Valley (Ministry of Home Affairs, 2010). In May 2010, a tragic incident occurred when Indian soldiers mistakenly identified three individuals as terrorists infiltrating from Pakistan and killed them. However, the situation escalated significantly when a rare subsequent police investigation revealed that the victims were innocent civilians (Bukhari, 2010). As a result, the summer of 2010 witnessed a highly violent conflict in Kashmir, resulting in the loss of 112 lives (Bukhari, 2010; Dar, 2010). Disturbingly, the majority of casualties were students (40%) and young adults[10] in their twenties (80%), distributed across all districts of Kashmir, including the Poonch district of the Jammu region (Dar, 2010). The unrest triggered a sudden surge in violence throughout the entire Kashmir Valley, with certain districts such as Baramula, Srinagar, Anantnag, Budgam, and Pulwama experiencing particularly intense levels of violence (Ministry of Home Affairs, 2010). The agitations sparked a cycle of violence, significantly disrupting the law and order situation in the State. The intensity of violence persisted throughout the duration until September, resulting in prolonged tension and the imposition of curfews in numerous locations within the Valley (Ministry of Home Affairs, 2010). Consequently, normal life was severely impacted, with ramifications such as the disruption of businesses, tourism, the closure of schools and colleges, and the non-functioning of civil governance institutions (Ministry of Home Affairs, 2010). The official data indicates that between January 2010 and May 2017, over 6,000 law and order incidents were reported, surpassing the approximately 2,000 occurrences related to insurgency during the same period (Parvaiz, 2017). Furthermore, there were approximately 13,000 incidents of stone-pelting in Kashmir between 2009 and 2019, with nearly 5,600 of them occurring solely during the mass uprisings of 2010 and 2016 (Ganie, 2021). We present the year-wise data on law & order cases and stone-pelting incidents in Figure 2a.

2.2 Education System and Learning Outcomes in Kashmir

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 December and for about two weeks for summer vacations, usually in June or July. Since the new form of violence took place in Kashmir in 2010, the education sector in Kashmir is periodically disrupted by the curfews, shutdowns (*hartals*), and other such law and order situations when schools remain closed for several months due to continuous shutdowns in major agitations (such as in 2010, 2016 and more recently in 2019). 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 a sudden school and college closures (Ministry of Home Affairs, 2010) for about four months[11]. Figure 2b shows the number of working days affected due to strike calls, curfews, and protest demonstrations. In 2010, 112 working days were affected to the mass unrest comprising most of the academic year, and this was the worst year in terms of working days affected to conflict in Kashmir in the recent past.

These school disruptions impair the student's learning and hence degrade the literacy and numeracy skills, which are already appalling throughout the country. In Figure 3, we compare the disparities in literacy and numeracy skills observed in Jammu & Kashmir across all grades

[10] The calendar year, 2010 has been called "The Year of Killing Youth". See Bukhari (2010) and Dar (2010) for a detailed account of the mass unrest.

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

(1-12) with those observed in the rest of India. The graph illustrates significant disparities in reading and math proficiency in the education systems of all the states. In rest of India, just about 38 percent of children in classes 1-12 can read a short story equivalent to a second-grade textbook, while only 28 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 competence in literacy and numeracy skills is significantly lesser when compared to the other Indian states, particularly Himachal Pradesh, Punjab, and Haryana. Only about 32% and 24% 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.

Appendix Figure A.5 depicts the relative grade-wise disparities in reading and math proficiency between Jammu and Kashmir and the rest of India for grades 1-12. 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 (see Figure A.1a). Similarly, the proportion of J&K students who are unable to solve a basic division problem is significantly higher than that of students outside of J&K (see Figure A.1b). These relative discrepancies in basic literacy and numeracy skills widen until the fourth grade and then appear to close[12]. The protracted Kashmir conflict could be one of the primary explanations for these significant learning disparities.

[Figure 3 about here]

3 Data and Descriptive Statistics

3.1 Data

In this paper, we use several rounds of the Annual Status of Education Report (ASER) — a survey to assess the learning of children in rural districts of India (Pratham, 2007, 2008, 2009, 2011, 2012). The ASER surveys a repeated cross-section of districts to obtain credible estimates of rural children's schooling status and fundamental learning levels in reading and arithmetic using rigorously developed testing tools[13]. Every year ASER randomly chooses 30 villages per district first and then 20 households per village are chosen at random for the survey. As a result, the sample size is 600 households per rural district or around 3,00,000 households at the national level[14].

The ASER data is unique due to its extensive sample size, which includes both enrolled and out-of-school children. Unlike other surveys where cognitive tests are typically administered within school settings, ASER encompasses children aged 5 to 16, irrespective of their enrollment status (enrolled, dropped out, or never enrolled). For our purpose, we focus on currently enrolled students in the main analysis, while the sample of out-of-school children is utilized to examine mechanisms in subsequent sections of the paper. Our dataset covers a five-year period, spanning from 2007 to 2012, excluding 2010[15], and consistently covers 14 districts of Jammu and Kashmir, representing all three divisions of the state (Jammu, Kashmir, and Ladakh)[16].

The ASER data possesses several distinctive features that make it particularly valuable for our analysis compared to other available datasets in India. Firstly, it stands out as the largest household survey dataset in the country[17], covering approximately 580 rural districts, including

[12] Gender wise learning gaps in reading and arithmetic are also reported. See Online Appendix Figures A.2

[13] See Appendix Figure A.6 for the ASER language and math test tools. For detailed overview of ASER testing tools, see https://asercentre.org/wp-content/uploads/2022/12/English_ASER-2018.pdf

[14] For more information on ASER sampling design, see https://asercentre.org/process-documents/

[15] 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 issues.

[16] The survey was not conducted in any of the Kashmir valley district in 2005 and for some districts in 2006.

[17] It is by far the largest survey data on learning outcomes, conducted annually in almost every rural district

surveys conducted in 14 districts of Jammu & Kashmir. This extensive coverage enables us to capture the variation in exposure to unrest across districts while effectively controlling for district fixed effects. By accounting for these fixed effects, we can effectively address any pre-existing differences in test scores that were unrelated to the unrest. Secondly, given that it is an annual survey[18], the ASER data allows us to capture conflict exposure over time and adequately adjust for year-fixed effects, thus accounting for common time trends. Thirdly, the survey administers reading and math assessments to all children between the ages of 5 and 16. This comprehensive approach provides variation in the age of students taking these tests and allows us to control for any shocks that may affect all children born in the same year by including birth cohort fixed effects in our analysis. These important characteristics of the ASER dataset enable us to capture variations in exposure to unrest across different time periods and geographical locations, while simultaneously accounting for district, year, and cohort effects, as well as district-specific linear time trends.

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, (s)he began with a paragraph (of grade one level). If the child could read the paragraph, (s)he was next asked to read a short story (of grade two level); if not, (s)he was instructed to read any five words. If (s)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 text). The test scores are coded as **1** if the child correctly answers the question and **0** otherwise. We generate a *"reading score"* variable 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[19].

Since these reading and math test scores take integer values only and are ordinal, treating them as interval scales could potentially lead to measurement errors[20] and interpretation of the treatment effects is also not very straightforward. For the ease of interpretation, 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[21]. These standardized scores serve

of India.

[18]Beginning from 2005, ASER was conducted annually till 2014. After that it is conducted every alternative year since 2016.

[19]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 Figure 3). Muralidharan et al. (2019) also document large learning deficits even for higher grade students in India.

[20]In our case, making comparisons across the treatment and control groups should not be dependent on the choice of scale, so we can still proceed with treating these outcome variables as interval scales as Shah & Steinberg (2017, 2021) and Chakraborty & Jayaraman (2019) do in their analysis with the same data. Nonetheless, our results are robust to using them as interval scales (results are available on request).

[21]The variables are standardized, for each subject, such that the mean and standard deviation in any given year is 0 and 1 respectively.

as dependent variables in our empirical estimations and the estimated regression coefficients can be interpreted as standard deviations[22]. As a robustness check, we later also estimate the treatment effects using the linear probability models for each reading and math level.

[Table 1 about here]

3.2 Descriptive Statistics

Table 1 presents the summary statistics of the test score variables, the reading and math scores and other important variables used in the study. The proportion of children who can read letters, words, paragraph (equivalent to grade one text) and a short story (equivalent to grade two text) progressively goes down as the difficulty level increases. While about 50% of the children could read a paragraph, only about 31% of children can read a short story. Similarly, the proportion of children who can recognize single digit numbers, double digit numbers and solve subtraction (equivalent to grade three text) and division problems (equivalent to grade four text) progressively goes down as the difficulty level of the test increases. Only about 23% of the children could solve a division problem. The average reading and math score is roughly 3. Given the ordinal nature of these test score variables, this number indicates that, on average, students can at most read at grade 1 difficulty level and not at grade 2 difficulty level; they can solve math problems at the grade 3 difficulty level but not at grade 4 level.

In our sample period, the average enrolment is about 97% while the rest 3% of children are out-of-school, who have either dropped out of school or never enrolled in school. The average child in our sample is around 10 years old and has completed about 5 grades. About 54% of the children in the sample are male, and the average household size is around 7 members. The mean age of mother and father is respectively 35 and 40 years, and around 39% of the mothers are literate.

[Figure 4 about here]

Figure 4 plots the distribution of the reading and math test scores. As can be seen from Figures 4a and 4b, children's learning levels are very low. The figure indicates that 16% of students are able to read letters but struggle to read at more advanced levels of proficiency. Furthermore, 22% of students can read a paragraph, along with letters and words, but face difficulties when reading a short story. Only a mere 37% of all children tested demonstrate the ability to read at the highest level of mastery. Similarly, in mathematics, 13% of students can recognize single-digit numbers but struggle with more advanced mathematical concepts. Additionally, 29% of students can solve subtraction problems and recognize both single and double-digit numbers, yet encounter challenges when attempting to solve division problems. Notably, just 28% of all the children tested display mastery in mathematics at the highest level.

4 Empirical Strategy and Identification

In this paper, our objective is to estimate the causal effect of exposure to civil unrest on learning outcomes, measured by the reading and math test scores. Our identification strategy exploits variation in exposure to conflict across space (districts) and time to estimate the effect of an individual's exposure to civil unrest on learning outcomes under a difference-in-differences design. As outlined in Section 2, only children in Kashmir valley were exposed to the violent civil unrest and children in other two regions of the state were not exposed to the violence. Hence, in our empirical strategy, children from districts of Kashmir make up the treated group and those from Jammu and Ladakh districts make up the control group.

[22]Existing studies using the same data have also standardized (normalized) these reading and math test scores to interpret them as standard deviations. For details, see Fagernäs & Pelkonen (2020); Banerjee et al. (2016); Krämer et al. (2021); Lahoti & Sahoo (2020).

We start by estimating the following specification for child i in district d surveyed in the year t and born in the year b,

$$y_{idtb} = \alpha + \delta_d + \delta_t + \delta_b + \delta_d * t + \beta(Kashmir_{id} * Post_t) + \theta \mathbf{X}_{idtb} + \epsilon_{idt} \tag{1}$$

where y_{idtb} is the test score outcome. The test scores y_{idtb} are standardized by year[23]. $Kashmir_{id}$ is a dummy variable which takes value 1 for child i from Kashmir district d and 0 otherwise. $Post_t$ is the dummy that takes value 1 for year $t > 2010$, the year of civil unrest. Specifically, it takes value 1 for years 2011 and 2012 and 0 for years 2007-2009. Note that these indicator variables are not included in the specification because their impacts are subsumed in the year and district fixed effects, respectively. The variable of interest in this specification is $Kashmir_{id} * Post_t$, which represents the chidren in districts of Kashmir valley in the post-unrest period. δ_d is a vector of district fixed effects, δ_t is a vector of survey year fixed effects, δ_b is a vector of birth cohort fixed effects. These sets of fixed effects account for differences in test scores by district, year, and birth cohort, respectively. We also include district-specific linear time trends ($\delta_d * t$), to allow for the evolution of test scores to linearly vary across years by district. The standard errors are clustered at the village level (the primary sampling unit in ASER dataset). The coefficient of interest is β, which captures the effect of exposure to unrest on test scores. X is a vector of controls which includes child's gender, grade, and household size. As a robustness check, we include some additional maternal controls such as mother's age, dummies for whether she attended school or not and the level of education (primary or higher education).

4.1 Identification

4.1.1 Parallel Trends Assumption

The identifying assumption underlying the difference-in-differences design is parallel trends, which in our case means that in the absence of the 2010 civil unrest, the test scores of children in treated Kashmir and untreated Jammu and Ladakh would have evolved in parallel to each other. Since parallel trends involve counterfactual outcomes, which we do not observe, directly testing the validity of parallel trends assumption is not feasible. However, one can compare the trends in outcomes of the treated and the control districts in the pre-treatment period to verify if the parallel trends holds in the pre-treatment period. Figure 5 plots the raw means of the reading and math test scores by treatment dummy in the pre-treatment period. Figure 5a shows the pre-trends for reading score and Figure 5b for the math score. These raw graphs depict that the treated and the control districts were not trending similarly in 2009. Figure 5 indicates that the parallel trends assumption, without conditioning on covariates, may be violated. We further test its validity using an event study by conditioning on covariates. We estimate the following specification,

$$y_{idtb} = \alpha + \delta_d + \delta_t + \delta_b + \delta_d * t + \sum_{t=1}^{t=T} \gamma_t \mathbf{1_t} * Kashmir_{id} + \theta \mathbf{X}_{idtb} + \epsilon_{idt} \tag{2}$$

where $\mathbf{1_t}$ is an indicator variable which takes value 1 if the child's test score outcome belongs to year t and 0 otherwise. In this specification, we use $t_0 = 2007$ as the base year and estimate the gaps in the test scores between treated and control groups in two-year bands. The coefficients of interest γ_t's provide the causal estimates of exposure to unrest before and after the unrest took place compared to the base year 2007. If γ_t's are statistically equal to zero, in the pre-treatment period, then it means that the two groups were trending similarly before the unrest took place.

[23] 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 in each subject. The dependent variables are thus the z-scores and estimated coefficients can be interpreted as standard deviations.

This test lends further support to the validity of parallel trends assumption. Appendix Figure A.3 presents the results from estimating equation 2. In Figures A.3a and A.3b, we find evidence of differential pre-trends. The coefficient of interest for the reading score in 2008/09 is not statistically significant but it is magnitudinally large. For math score, we find statistically significant coefficient in 2008/09 which is also magnitudinally large.

[Figure 5 about here]

The existence of pre-treatment trends in learning outcomes could spuriously bias our main results. In addition, we cannot also interpret our main results as causal. We deal with this violation of parallel trends in section 7 by showing the sensitivity of the causal estimates to the violation of parallel trends as suggested by Rambachan & Roth (2023). However, for our main analysis, we restrict our sample to the districts for which the parallel trends assumption holds. We proceed by checking the pre-trends for each individual district one-by-one and then retain all those districts for which it holds (see Online Appendix B). Unsurprisingly, the districts for which the parallel trends does not seem to hold largely share the borders with Kashmir districts and therefore point towards the possible spillover effects of violence. Consequently, we drop these districts from the analysis to minimize concerns of spillover effects of violence. Figures 6a and 6b plot the raw means by treatment indicator, which now takes value 1 for all districts of Kashmir and 0 for Jammu, Rajauri, Leh(Ladakh) and Kargil districts of Jammu and Ladakh regions[24]. Notice that we have left out other districts for which the parallel trends did not hold. Looking at the differences in raw means between the treated and control groups, it seems that the parallel trends assumption holds. To further confirm this, we present results from estimating event study specification 2 in Figure 7. Figures 7a and 7b show no evidence of pre-trends. Compared to the base year 2007, the coefficient of interest for the year 2008/09 is magnitudinally small and statistically insignificant for both the reading and math score.

[Figure 6 & 7 about here]

Further, we also present results from a falsification test in Table A.1 where we assign year 2009 a pseudo post status. In other words, we restrict our sample to pre-unrest period (2007-09) and present results from estimating equation 1 by assuming that the unrest happened in the year 2009. If the two groups were trending similarly in the pre-unrest period, the coefficient on the interaction term should not be statistically significant. In columns 1 and 2 of Table A.1, we do not find a statistically significant effect on reading score. The coefficients are also smaller. We find similar results for the math score in columns 3 and 4. These null findings lend further support to the validity of parallel trends. As a further robustness check, we also report results in section 7 using an alternative identification based of Figures 6c and 6d, where we retain only two control districts, namely Jammu and Rajauri, for which the parallel trends also holds.

4.1.2 Endogeneity

A plausible concern with our identification strategy is that the timing of the unrest may be correlated with the trends in test scores. Although, we include the district fixed effects to control for time-invariant district level characteristics, we may still be concerned that time-variant district specific characteristics could be correlated with trends in test scores. Including the district-specific linear time trends in our baseline specification could, in part, address this concern of potential endogeneity. However, to further test these potential endogeneity concerns, we check for pre-unrest correlations between the test scores at the district level and assignment to treatment. In other words, we check if there are significant differences in test scores at the district level between the treated and the control districts. Besides, we also check for difference in other pre-unrest characteristics. To this end, we collapse our reading and math test scores at the district level to compute average reading and math test score for each district and then regress these average test scores on the treatment dummy. Results are reported in columns 1

[24]Refer to Figure 1b to see which all districts are taken as control districts for the main analysis of the paper.

and 2 of Appendix Table A.2. We find no statistically significant correlations in either reading score (column 1) or math score (column 2). This null finding further strengthens the confidence on our causal estimates.

Further, to provide more confidence on our results, we also analyze pre-unrest correlations between the treated and control districts using other important characteristics such as confidence in government, politicians, police, schools and courts. These are important because if there exist significant differences between treated and the control districts on these variables concerning public policy, quality of schooling and delivery of justice, then we could be capturing the effect of school quality or it could be the case that people were dissatisfied or distrustful of the public policy which triggered the civil unrest of 2010[25]. To analyze these correlations, we use the first wave of the Indian Human Development Survey (IHDS-1), conducted in 2004/05. IHDS samples households from 3 Kashmir districts and 2 Jammu districts and collects information on social capital such as trust and confidence on government, schools, hospitals, etc[26]. We again collapse these variables at the district level to compute district averages and then regress them on the treatment dummy. Results are reported in columns 3-7 of Appendix Table A.2. We find no statistically significant correlations in almost all of the social capital variables. If anything, households in treated Kashmir have, on average, more confidence in the government — the positive correlation is statistically significant. Households in Kashmir also seem to have higher confidence in local politicians and police as well as courts to deliver justice. However, the positive coefficients are not statistically significant.

Another concern with our identification strategy is that our results could be driven by something other than the exposure to civil unrest. For instance, it could be the case that districts which are impacted by violent conflict are also districts which are poor and thus we may be picking up the effects of poverty rather than the exposure to unrest. To probe this, again we use the IHDS-1 data and check if there are any significant correlations between average district-level per-capita consumption expenditure and proportion of people living below poverty line and being assigned to the treatment. Results are reported in columns 8-9 of Appendix Table A.2. We do not find any statistically significant correlation between these measures of poverty and assignment to treatment.

5 Main Results

5.1 The effect of civil unrest on learning outcomes

Table 2 presents the results from estimating specification 1 separately for reading and math score. The dependent variables in columns 1-4 and columns 5-8 are standardized reading and math scores, respectively[27]. Thus, our outcomes of interest are the z-scores of academic achievement rather than the absolute achievements. Columns 1 and 5 show the results from the most basic version of estimating equation 1, which includes only the district and year fixed effects. Column 1 shows that the exposure to civil unrest is associated with a decline of 0.07 standard deviations in reading score and column 5 shows a decline of 0.122 standard deviations in math score. However, the effect is not statistically significant for the reading score but it is statis-

[25] As mentioned in the background section, the civil unrest of 2010 was triggered by the killing of three civilians who were perceived as terrorists sneaking in from the international border. However, they were later proved innocent in an unprecedented police probe which later led to this mass unrest. Also, towards the later half of the unrest, the incident of burning of the Holy Quran in the United States intensified the unrest (see https://www.theguardian.com/world/2010/sep/13/kashmir-protesters-killed-quran-row). Therefore, it is quite unlikely that the timing of the unrest was endogenous.

[26] The survey asks the households the amount of confidence they have on government (to look after the people), schools (to provide good education), courts (to meet out justice), etc. They can answer in three ways: great, some or hardly any confidence.

[27] Remember that we have standardized the reading and math score by year such that the mean and standard deviation in any year for each test score variable is 0 and 1, respectively.

tically significant at 5% level for math score. Columns 2-4 and 6-8 show that the negative effects of civil unrest are robust to the inclusion of birth cohort fixed effects (columns 2 and 6), district-specific linear time trends (columns 3 and 7) and bunch of control variables such as the gender of the child, the grade of the child and the household size (columns 4 and 8). As we progressively estimate the stricter versions of estimating equation 1 in columns 2-4 and 5-8, the negative effects of exposure to unrest increase in magnitude as well as statistical significance. Using our preferred specification in columns 4 and 8, we find that the exposure to civil unrest reduced the reading and math test scores by 0.543 and 0.369 standard deviations, respectively. These negative effects of violence are statistically significant at 1% level.

[Table 2 about here]

Since the primary objective of the ASER surveys is to collect information on the schooling status and learning outcomes, in its initial years it did not extensively collect information on other background characteristics. Therefore, we cannot additionally control for other variables in our analysis while maintaining the sample size intact. Nonetheless, in Appendix Table A.3, we show that these negative effects of violence are also robust to additional maternal level controls such as mother's age, whether or not she has attended school and her level of education (primary school or higher). Columns 3 and 6 show that the negative effects remain statistically significant at 1% level and they also remain magnitudinally stable. However, after controlling for these additional background variables, we lose a significant number of observations.

The negative treatment effects of exposure to violence that we document in Table 2 are larger in terms of the magnitude when compared to other closely related studies examining the impact of conflicts on student achievement. For example, Monteiro & Rocha (2017) find a 0.054 standard deviation reduction in math score but no effect on reading score 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 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. Ang (2020) finds that the police violence in United States is associated with a decline of GPA by 0.03 standard deviation, on average. In Colombia, Gómez Soler (2016) finds adverse effects of civil conflict in the range of 0.15 standard deviations in math and 0.08 standard deviations in language using the pseudo panel estimation. 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). Bharadwaj et al. (2021) is the only related study which finds the similar large negative effects of violence (about 0.5 standard deviations) on exam performance in Norway[28].

To put our main findings in perspective, the negative effects of unrest on reading and math test scores that we document could account for a fall in test scores equivalent to about 1.5 times (for reading) and about one times (for math) the fall in test scores associated with a one standard deviation decrease in teacher quality as documented in literature for India by Azam & Kingdon (2015). Further, compared to randomized control trails in India aimed at improving student test scores, these negative effects are much higher than the gains in student learning achieved from these interventions. For instance, after two years of exposure to a math computer-assisted learning programme, primary-school students in urban India scored 0.47 standard deviations higher in math (Banerjee et al., 2007), while after 4.5 months of targeted technology-aided after-school tutoring, middle school students scored 0.36 standard deviations higher in arithmetic

[28]Similar to their paper, as discussed in Section 2, in our context, students and young adults were the most vulnerable population. Thus, these large negative effects could be a direct result of trauma, psychological stress etc. While Bharadwaj et al. (2021) do not show the channels linking the deterioration in exam performance to gun violence, we investigate the underlying mechanisms in Section 6.

and 0.22 standard deviations higher in Hindi (Muralidharan et al., 2019). Moreover, 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. These findings from the literature suggest that the negative effects of exposure to unrest may stubbornly persist and it may be difficult to compensate for the loss via these interventions.

[Table 3 about here]

Table 3 shows the persistence of these negative effects of violence. Table 3 presents the results from estimating equation 1 by breaking the $Post_t$ dummy into two. $Post_1$ takes value 1 for post-unrest year 2011 and 0 otherwise. Similarly, $Post_2$ takes value 1 for post-unrest year 2012 and 0 otherwise. Columns 1 and 4 report our main results from specification 1. In columns 2 and 5, we replace the $Post_t$ dummy by $Post_1$ and $Post_2$ to check for persistence of negative effects of unrest. Column 2 shows that the negative effect of violence on reading score persists to 2012 and remains statistically significant and magnitudinally stable. Column 5 shows the same result for math score. Columns 3 and 6 show that these persistent effects are robust to the inclusion of controls. These results suggest that the exposure to conflict can have persistent negative effects on learning outcomes. These large and persistent negative effects of civil unrest could plausibly be explained by spillover effects of violence. For instance, Bharadwaj et al. (2021) find spillover effects of violence exposure on siblings who were not directly impacted by the mass shooting in Norway. They find that the test score of siblings of directly exposed children in the middle school reduces by about 0.2 standard deviations. In addition, Padilla-Romo & Peluffo (2023) also show that violence exposure leads to negative spillovers (via out-migration) to areas not affected by violence. They show that non-exposed students in receiving school who attend classes with children exposed to violence score around 0.02 standard deviations lower.

5.1.1 Heterogeneous effects of civil unrest on learning outcomes

Next, we investigate the heterogeneity in treatment effects of exposure to violence by grade levels — primary, middle and secondary — gender, socioeconomic status and the type of school the child attends — government or private school. Table 4 presents results from estimating equation 1 separately for children in primary school (grades 1-5), middle school (grades 6-8) and secondary school (grades 9-12). We show in Appendix Table A.4, using a falsification test, that there were no pre-trends for each of these sub-groups. Columns 1-3 and 4-6 of Table 4 report heterogeneous effects for each of the three sub-groups separately for reading and math tests, respectively. Column 1 shows that conflict had negative and statistically significant effect on reading score of primary school children, while the negative effect on math test score is not statistically significant at the conventional levels of significance (column 4). Documenting large negative but no statistically significant effect on math test score for the primary school children could be explained by the fact that these students are yet to master advanced levels of mathematics. Therefore, exposure to conflict does not potentially affect their math performance. To confirm this, we estimate equation 1 separately using each of reading and math test level in Appendix Table A.14. Panels A, B and C show the effects for primary, middle and secondary school children, respectively. In line with our plausible explanation for null effects in math score for primary school children, the conflict has null effect only at higher levels of mastery in mathematics.

Columns 2 and 5 of Table 4 show that conflict had the largest adverse effects on the children in grades 6-8 for whom the negative effects are statistically significant at 1% level. These students are expected to have mastered these reading and math skills by classes 6-8. Interestingly, columns 3 and 6 show that exposure to conflicts also had negative and statistically significant effects on high school students. Yet, the effects are much higher for the younger students in grades 1-8 — this finding is crucial in ruling out any potential endogeneity concerns due to selection issue. Since younger students in grades 1-5 and 6-8 (who are typically aged 5-13) are very less likely to self select into violence, selection into violence is less likely to bias our results. This finding in consistent with literature which finds larger effects of drug-related violence in Mexico on younger students (Michaelsen & Salardi, 2020).

[Table 4 about here]

Table 5 presents results from estimating equation 1 by gender of the child, the type of dwelling a child resides in (a proxy for socioeconomic status) and the type of school a child attends. Again, we show in Appendix Table A.5, using a falsification test, that there were no pre-trends for each of these sub-groups. Panel A present results from estimating equation 1 separately for male and female students (columns 1, 2, 4 and 5). The results indicate that conflict had negative and statistically significant effects for both genders in reading (columns 1 and 2) and math (columns 4 and 5). In columns 3 and 6, we test for differential gender effects of exposure to conflict using a triple-difference design. We find no statistically significant differential effects by gender on either of the test score variables. In fact the coefficient of interest on the triple differences specification is very close to zero. There is mixed evidence in the literature on gender differential effects of violence. While some studies find that boys are more adversely impacted (Ang, 2020; Koppensteiner & Menezes, 2021), other studies find no gender differential effects (Monteiro & Rocha, 2017; Brück et al., 2019). Our finding that civil unrest has no gender differential effects suggests that the mechanisms driving these results are gender neutral.

Panel B shows the effects separately for children who reside in *Pucca* (concrete) houses and those who reside in *Kutcha* (made of mud) houses. Columns 1 and 2 show that conflict adversely effects the reading score of both the sets of students. However, the negative effect is higher for children with high socioeconomic status. Column 3 shows that the differential effect is not statistically significant. Columns 4, 5 and 6 show similar results for math score. These findings suggest that the mechanisms which drive the main results are independent of the socioeconomic status of the student. For instance, if conflict negatively affects family incomes which could in turn affect test scores, we should then see the detrimental effects only for students from low socioeconomic background. Yet, we find that both the sets of students are equally impacted by the spate of violent conflict.

Finally, Panel C shows the effects separately for students enrolled in private and public schools. The evidence of private school advantage in the Indian setting is well documented (Chudgar & Quin, 2012) and the general belief is that students in private schools have superior educational achievements to those in public schools. Furthermore, existing literature shows that government school children are more affected by violence (Brück et al., 2019). Columns 1, 2, 4 and 5 show that conflict impacts both the private and public school students but the effects are greater for low-performing public school children. Columns 3 and 5 show that the differential effect is positive but not statistically significant at the conventional levels of statistical significance. This finding points to the fact that the mechanism that may explain the detrimental effects of violence is most probably not the school closures. Since, if it was about the closure of schools and the associated loss of instructional time, then we should not see statistically significant effects for kids in government schools, assuming that children enrolled in public school do not benefit much from school instruction given their quality[29]. On the contrary, we document larger effects for them. We investigate the plausible underlying mechanisms in the following section.

[Table 5 about here]

[29]Since we know that students in public schools learn much lesser than their private school counterparts, this is the extreme case where we assume that the quality of public schools is so worse that students do not benefit at all from school instruction.

5.2 Additional Results

5.2.1 The distributional effects of civil unrest on learning outcomes

We investigate the heterogeneity in treatment effects along the test score distributions so as to understand which sets of students drive the main results. Understanding the distributional consequences of exposure to violence is crucial from policy perspective so as to design coping mechanisms which are more targeted towards the most vulnerable groups of students. To test for the treatment effect heterogeneity along the test scores distribution, we use the quantile regression model[30] (for details, see Koenker & Hallock (2001)) and report results in Table 6. In column 1, we present our main results for each test score variable in panels A and B. The quantile regression results in columns 2-6 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. In contrast to our main findings in Table 2 and Table 4, the quantile regression results show that the unrest does not affect students in the upper tail of the test score distribution.

These findings from the quantile regression suggest that exposure to civil unrest can exacerbate the existing learning disparities between the low and the high performing students. The negative effects of civil unrest on low-performing students can have significant long-term implications. Lower test scores may hinder their academic progress, limit their educational opportunities, and impact their future prospects. Further, they can potentially have negative impact on their graduation rates, employment prospects, and overall socioeconomic mobility. Therefore, there is a greater need to design policies which are aimed at these low-performing kids so as to ensure equitable education and equal opportunities for future prospects.

[Table 6 about here]

5.2.2 The effect of civil unrest on school enrolment and drop-out rates

We investigate the effects of violent conflict on school enrolment in Table 7. The dependent variable is an indicator variable which takes value 1 if the child i is currently enrolled in school and 0 otherwise[31]. In column 1, we present the result from the most basic version of estimating equation 1 which includes no fixed effects and controls. The coefficient of interest on the interaction term is very close to zero and statistically insignificant. Columns 2-5 show that this null effect is robust to the inclusion of controls, district, year and birth-cohort fixed effects, respectively. However, once we include the district-specific linear time trends in our model (column 6), the negative effect considerably increases in magnitude and becomes statistically significant at 5% level. Using our preferred specification, we find that exposure to civil unrest reduces the probability of enrollment by 2.3 percentage points. This result indicates that children delayed joining schools in Kashmir (relative to Jammu and Ladakh) in the post treatment period as compared to the pre-treatment period. One plausible explanation to this delayed school start could be that parents were concerned about the safety of their children. As mentioned in Section 2, the probability of being killed was higher for students which must have had generated a general sense of fear and insecurity among the population. Therefore, it is possible that parents were waiting for things to get better before they decide to send the children to school.

[Table 7 about here]

Next, we investigate the effects of violent conflict on the probability of dropping out of school in Table 8. The dependent variable is an indicator variable which takes value 1 if the child i has dropped out of school and 0 otherwise. Column 1 presents the result from the most basic version

[30] We estimate the effects using the *sqreg* command in Stata, which estimates the effects for each quantile and estimates the variance–covariance matrix (VCE) via bootstrapping using the between quantile blocks.

[31] To analyse the effects of conflict on school enrollment and drop-outs, we extend our original sample to include the out-of-school children in the data. They were earlier dropped from the sample. The dependent variable takes value 0 for such children in the data.

of specification 1 which includes no fixed effects and controls. The coefficient on the interaction term is statistically insignificant and magnitudinally very close to zero. Columns 2-6 show that this null effect is robust to the inclusion of controls, district, year and birth-cohort fixed effects as well as district-specific linear time trends, respectively. This finding could probably explain the persistence of the adverse effects of violent conflict in Table 3. If children exposed to violence do not drop out of school and the quality of schooling deteriorated or children suffered from psychological stress, then negative effects are more likely to persist over time.

These null effects of civil unrest on the likelihood of dropping out of school in the post period compared to pre-unrest period in Kashmir (relative to the control districts of Jammu and Ladakh) also signify that students do not plausibly move out of the violence affected region. This is an important finding because selective migration could act as a potential threat to our identification. For instance, if high-performing students are more likely to migrate out of treated Kashmir in the post-unrest period, then we may be left with a selected sample of students, who chose to not move. In this case, it is possible that we may be picking up the effects of deterioration in the pool of test-takers rather than the effect of exposure to violence on academic achievement. However, this is not likely to be the case because, in the event of relocating out of a violence-affected region, students have to drop out of school, of which we find no evidence in the data. Moreover, the IHDS-1 and 2 datasets suggest that the households in the violence affected rural areas of Kashmir districts do not migrate in very large numbers[32]. Data from IHDS-1 (2004/5) shows that 99% of the households in rural districts of Kashmir valley did not migrate out of Kashmir. Similarly, data from IHDS-2 (2011/12) shows that about 93% of rural households in Kashmir did not migrate out. Therefore, our results are very less likely to be confounded by selective migration.

[Table 8 about here]

6 Mechanisms

To this point, we have demonstrated that exposure to civil unrest of 2010 in Kashmir had a large negative (average) effect on students' reading and math test scores. We also showed the distributional effects of exposure to violent unrest. In this section, we explore possible transmission channels through which exposure to conflict can affect the performance on basic literacy and numeracy tests.

6.1 School closures and learning outcomes

One of the important transmission mechanism linking conflict and learning outcomes could be the amount of time spent in school, which is one of the important determinants of students' academic achievement. As mentioned in Section 2, the unprecedented violent civil unrest of 2010 in Kashmir led to prolonged school closures (Ministry of Home Affairs, 2010), which lasted for about 4 months[33]. Figure 2b also shows that in 2010, 112 working days were affected due to civil conflict in Kashmir valley. Previous research has shown mixed evidence on whether school closures can explain the negative effects of violence on academic achievement. While some studies find it to be an important channel linking conflict to academic performance (Monteiro & Rocha, 2017), other do not find any evidence of it to be mediating the negative effects of violence (Brück et al., 2019).

[Table 9 about here]

[32]Since, ASER only surveys households from the rural areas of the districts of the country and therefore of Kashmir, we check for the number of years the household has been residing in its place of interview in IHDS-1 and 2 datatsets because of unavailability of this information in ASER. We report the figures of households who have stayed in Kashmir forever.

[33]According to the newspaper reports, the schools were shut for nearly 4 months. See https://www.indiatoday.in/india/story/schools-reopen-in-kashmir-valley-after-4-months-82724-2010-09-26

To test if school closures is the main channel driving our main results, we examine the effect of school closures on learning outcomes in Table 9. As pointed out in Section 3, for our main analysis, we restricted data to the currently enrolled students only. However, the advantage of ASER dataset is that is includes both currently enrolled students and out-of-school students (drop-outs and never-enrolled students). In Table 9, we estimate equation 1 on out-of-school students to check if exposure to violence has similar negative and statistically significant effects on this set of students. Since, these are out-of-school children, school closures due to conflict should not have an impact of their academic achievement. Table 9 shows that the point estimates are larger in magnitude (since we only have a limited number of observations, these points estimates may not be precisely estimated) but are not statistically significant across specifications. Using our preferred specification in columns 3 and 6, we do not find any robust evidence of school closures in mediating the negative effects of civil conflict on learning outcomes.

6.2 Student absenteeism and learning outcomes

Another possible mechanism which could explain the negative effects of violence on student performance is the student absenteeism. Exposure to violent conflicts could lead to increased student absenteeism which in turn could lead to a worsening of test scores — via the loss of instruction at school. As long a children benefit from instruction at school, missing school for a long time could translate into fall in test scores. We test for this mechanism in Table 10. Since, we do not have data on student attendance to directly test for this mechanism, we exploit heterogeneity in treatment effects by maternal education. We posit that children whose mothers are educated should not be affected by violent conflict if the channel linking violence to test scores is student absenteeism or more generally the loss of instruction at school. In the event that the child is away from school for an extended length of time, the educated mothers should be able to engage them in learning in home as compared to the uneducated mothers. Therefore, violence should have no or very small effect on these children.

In Table 10, we present results from estimating equation 1 separately for children whose mothers have or haven't attended school (literate mothers) in Panel A and for children whose mothers have more than or less than primary school education (educated mothers) in Panel B. Columns 1 and 2 of Panel A show that the conflict negatively affects the reading performance of both the groups of students, however the effect is smaller for students with literate mothers. In column 3, using the triple differences specification, we test if the differential effect is statistically different from zero. We do not find any significant differential effect of conflict for children with literate mothers. Columns 4 and 5 show that conflict has a negative effect on the math performance of both the groups but the effect is not statistically significant for students with illiterate mothers. Yet, the magnitude of the effect is larger for the set of students whose mothers have attended school. Column 6 shows that the differential effect is not statistically significant at the conventional levels of significance.

[Table 10 about here]

In panel B of Table 10, we find that the exposure to civil unrest has large negative effect on reading score of children whose mothers have only primary education (column 2) as compared to children whose mothers have more than primary education (column 1). However, the differential effect is not statistically significant (column 3). We find more or less similar results for math score in columns 4-6. These heterogenous treatment effects of violence exposure suggest that the student absenteeism or more generally the factors which cause loss of instruction in school (such as school closures) are plausibly not the underlying mechanisms which explain the negative effects of violence on reading and math test score. The findings in Table 10 support the findings in Table 9 to rule out the role of school closures, student absenteeism or other channels which cause loss of instruction at school in explaining our main results.

6.3 Effect of civil unrest on quality of schooling

Next, we investigate the role of quality of schooling as a possible underlying mechanism. The quality of schooling may include a bunch of variables such as quality of teaching, teacher absenteeism, and more generally changes in the quality of school learning environment such as loss of infrastructure, safety and security of children in school, etc. Conflict could lead to deterioration in the quality of schooling via the worsening of the teaching quality (for example, via the attrition of qualified teachers in the post conflict period), increased teacher absenteeism or due to changes in the learning environment in school. All of these can in turn have a negative affect on the child's reading and math test scores. The existing literature has shown that conflict adversely affects student performance via increase in teacher absenteeism and attrition (Monteiro & Rocha, 2017; Jarillo et al., 2016), changes in the quality of learning environment in schools (Brück et al., 2019) and damage of school infrastructures (Kibris, 2015).

To test if the quality of schooling is the potential underlying mechanism which may mediate the negative relationship between exposure to civil unrest and learning outcomes, we employ the IHDS-1 and 2 household datasets. As mentioned in Section 4, IHDS collects information on social capital such as trust and confidence on government, schools, hospitals, etc from sampled households. We estimate the effect of conflict on the probability of households reporting having great confidence in schools using a difference-in-differences design as in equation 1, where the dependent variable is an indicator taking value 1 if households report having great confidence in schools and 0 if they report having only some confidence in schools[34]. Table 11 presents the results from estimating an equation similar to our main specification 1 using this confidence indicator variable as the dependent variable. Column 1 presents the results from the basic version of the specification, which does not include any fixed effects. The coefficient on the interaction term ($Kashmir_{id} * Post_t$) is negative and statistically significant at 5% level. In terms of magnitude, the quality of schooling — measured by the confidence in schools to provide good education — deteriorated by 25 percentage points in Kashmir districts (compared to Jammu districts) in the post-unrest period relative to the pre-unrest period. Columns 2-5 show that the negative effect of conflict on school quality is robust to the inclusion of district, wave, caste and religion fixed effects as well as the district-specific linear time trends. As we estimate the stricter versions of the estimating equation in columns 2-5, the magnitude of the treatment effect remains largely stable but the effect is now statistically significant at 10% level.

[Table 11 about here]

Since ASER only includes rural sample of children, we present the results separately for the urban and rural sub-samples in columns 6 and 7. Column 6 shows that conflict has no statistically significant effect on school quality in urban areas — in fact, the coefficient of interest is positive but close to zero. In contrast, the quality of schooling in rural areas deteriorated by 23.3 percentage points and the effect is statistically significant at 10% level. Overall, we find (weak) evidence of diminished quality of schooling in post-unrest Kashmir (compared to Jammu) relative to the pre-unrest quality of schooling[35]. Therefore, quality of schooling could be a mediating channel linking civil unrest to learning outcomes in Kashmir.

[34] In IHDS-1, the survey asks for the confidence in schools whereas in IHDS-2 it asks for the confidence in public and private schools separately. For our purpose, we generate a common variable, *confidence in schools*, by assigning a value 1 to it if households report confidence in both public and private schools in IHDS-2 and 0 otherwise. The question specifically asks the respondent 'what deal of confidence you have in schools to provide good education' (a great deal, only some or hardly any confidence).

[35] In appendix Table A.6, we show results using an indicator variable that takes value 1 if household reports having great confidence in schools and 0 if they report having hardly any confidence in schools. We find null effects across specifications. The point estimates are closer to zero and not statistically significant. This suggest that the quality of schooling has not deteriorated to the point that parents have no confidence at all in schools to provide good education.

6.4 The role of fear, uncertainty and insecurity: Psychological distress

Finally, we test the role of psychological and mental well-being as a potential mechanism linking exposure to violence to worsening of learning outcomes in Kashmir. Child's psychological well-being is an important determinant of learning. Exposure to violent conflict can lead to a worsening of academic performance due to the lack of focus associated with fear and insecurity that is inflicted by conflict (Gershenson & Tekin, 2018). As pointed out in Section 2, a majority of causalities in the summer unrest of 2010 were students and young adults in their 20s; in such an environment, the probability of death (especially for young students) is higher. It is reasonable to assume, under such conditions, that exposure to the unrest (either directly or indirectly via the death of a family member, relative, neighbour or a colleague) might have led to the heightened psychological stress and deterioration in the mental well-being (Gershenson & Tekin, 2018).

According to Ang (2020), being exposed to police violence increases a student's risk of emotional disturbance by 15% in the United States, and in the year after the violence, they are twice as likely to report feeling unsafe in their surroundings. He also finds that these students experience a fall in their GPA by 0.08 standard deviations which lasts for few semesters. In Mexico, Michaelsen & Salardi (2020) find that drug-related violence is associated with a 0.1 standard deviation drop in exam scores which they attribute primarily to acute psychological stress. Similarly, Brück et al. (2019) find some evidence of psychological well-being as an underlying channel that plays an important role in mediating the negative effects of conflict in the West Bank on the likelihood of passing the final exams for high school students, while Shany (2023) also attributes the reduced exam performance due to terror attacks in Israel to psychological impacts.

Although we cannot directly test for this mechanism because of lack of data, we provide suggestive evidence that it is plausibly the channel which explains the negative and persistent effects of civil unrest of 2010. To this end, we investigate if violent conflict of 2010 affected the likelihood of availing private tuition. Since, we find some evidence of reduced school quality in Table 11, we should see an increase in access to private tuition to offset deteriorating effects of school quality on academic performance. On the contrary, if conflict causes a general sense of insecurity, fear, uncertainty, anxiety and depression in students and parents, then we should not find any positive and statistically significant effect of violence exposure on access to private tuition. Rather, if parents attach a higher probability to death or harm to their kids in the event of going outside of homes, then we should actually find a negative and statistically significant effect of civil unrest on access to private tuition. This will reinforce our belief that conflict led to increase in fear, insecurity and psychological stress among kids as well as parents.

We present results from estimating specification 1 using an indicator variable that takes value 1 if child i in district d born in year b and surveyed in the year t avails private tuition and 0 otherwise in Table 12. We use ASER data to quantify the effect (at the extensive margin) of civil unrest on probability of availing paid private tuition. Column 1 includes only the district and year fixed effects and no other controls or fixed effects. The coefficient on the interaction term is negative and statistically significant at 1% level. In terms of magnitude, exposure to civil unrest reduces the probability of availing private tuition by 16.6 percentage points. Column 2 shows that this negative effect is robust to the inclusion of birth cohort fixed effects. However, once we also include the district-specific linear time trends in column 3, the size of the negative effect diminishes in magnitude and the effect is no longer statistically different from zero. Column 4 shows the similar result when we control for other variables. Nonetheless, we do not find any positive effects of civil unrest on the uptake of paid private tuition facilities to offset the worsening effects of school quality.

[Table 12 about here]

We find some evidence of reduced demand for private tuition in Table 12. This finding points towards the fact that conflict might have generated fear and insecurity among both the students and parents so that they respond to it by reducing the demand for after-school private tutoring. To further confirm this, we employ the IHDS-1 and 2 individual panel dataset to estimate the effect of conflict on after-school paid private tuition (at the intensive margin). The dependent variable is the hours of private tuition per week. We present the results in Appendix Table A.7. Column 1 includes the district and wave fixed effects as well as district-specific linear time trend. The coefficient on the difference-in-differences interaction term is negative and statistically significant at 10% level. In terms of magnitude, exposure to conflict reduces the private tuition by about 2 hours per week. Column 2 shows that this negative effect is robust to inclusion of controls such as gender of the child, income, distance to school, poverty status, area of residence (rural or urban), household size, highest education of the household member, age fixed effects and religion fixed effects. In columns 3 and 4, we replace district fixed effects by individual fixed effects. The size of the negative effect decrease and is no longer statistically significant (column 4). However, we still find some evidence of reduced demand for paid private tuition at the intensive margin. Together, Tables 12 and A.7 imply that conflict led to a reduction in the demand for after-school paid private tuition both at the extensive and intensive margins. This raises our confidence that the mechanism driving our main results is the psychological stress caused by increased sense of insecurity, fear and anxiety due to violent conflict.

7 Robustness

In this section, we present a battery of robustness checks. First, we start by showing that our main results are robust to alternative way of clustering the standard errors. Throughout the paper, we have clustered the standard errors at the village level, the primary sampling unit in ASER. In Appendix Table A.8, we present our main results by clustering standard errors by district-year and district-birth year. In columns 1, 2, 5 and 6, we cluster standard errors by district-year and in columns 3, 4, 7 and 8, we cluster standard errors by district-birth year. The results indicate that the negative effects of violent civil unrest (as documented in Table 2) remain statistically significant across specifications for both the reading and math test score variables.

Since our reading and math test score variables are ordinal in nature, treating them as interval scales could lead to measurement error and the interpretation of the treatment effects is also not very straightforward. Consequently, in our main analysis, we standardized these test score variables and presented the results using z-scores. As a robustness check, we estimate the effect of civil unrest on learning outcomes using an alternative specification. We present results from linear probability models separately for each of the eight components of reading and math tests in Table 13. The dependent variable in each of the eight columns of Table 13 is an indicator variable which takes value 1 if the child has achieved the level of mastery as indicated by the model labels. The results from Table 13 confirm the negative effects of civil unrest. The exposure to civil unrest reduces the likelihood of being able to read words, paragraph and a short story. It also decrease the probability of being able to solve simple subtraction and division problems[36]. Appendix Table A.14 presents grade-wise heterogeneity in treatment effects based on this alternative specification.

[Table 13 about here]

Related to the previous robustness check, we also present results with a common test score variable, the total test score, which is obtained by adding the reading and math test scores for each child. This total test score variable generates more variability than either of the two test score variables individually — it takes values from 0 to 8. Hence, we consider it as a continuous variable (on a interval scale) and estimate the effect of conflict on it using the OLS. In Appendix

[36]We get similar results when we use *Probit* model instead. The results are available upon request.

Table A.11, we present results using this total test score variable as the dependent variable in columns 1-3 and it's standardized version[37] in columns 4-6. The results in columns 1-3 suggest that unrest negatively impacted the total test score and the effect is statistically significant at 1% across specifications. In terms of magnitude, the civil unrest decreased the total test score by 1.053 points (on a scale of 0-8). This translates into a fall of 18.84% of the mean of the dependent variable. The negative and statistically significant effect of violence on standardized total test score in columns 4-6 confirm our results in Table 2.

In our main specification 1, we account for the fact that different cohorts of children may be exposed to different levels of exposure to violence by including birth-cohort fixed effects. For instance, older children may be exposed to civil conflict differently than younger children if exposure to violence increases psychological stress. In addition, by including cohort fixed effects, we also take care of the fact that older students (in classes 9-12) are more likely to pass the basic literacy and numeracy tests in ASER surveys. However, we may still be concerned that different cohorts of children in different districts of residence might have different exposure to early life shocks which can impact their test scores. For instance, as discussed in Section 2, the armed conflict in Kashmir started in the early 1990s and involved higher number of civilian casualties over the course of about 10 years. Parlow (2011) finds the negative effect of insurgency on years of education completed by school-age children in urban Kashmir[38]. Besides, there was a war fought between India and Pakistan in 1999 which is also found to have negatively impacted educational attainment[39](Bharati, 2022). To alleviate these concerns, we include in our main specification 1 the district-cohort fixed effects. Appendix Table A.12 shows that the results are in line with our main results. After including district-cohort fixed effects, the negative effects of civil unrest modestly increase in magnitude and remain statistically significant at 1% level (columns 2 and 4). Therefore, even if we do not account for the district-cohort fixed effects in our main specification, if anything, we might be underestimating the true effects of violence on test scores.

The next robustness check concerns the issue of selection into violence. We briefly discussed in Section 5 that endogeneity due to selection is unlikely to be driving our results by showing that civil unrest of 2010 has negative and statistically significant effect on the test scores of young children in primary and middle schools who are young enough to select into violence. Besides, we also showed the effects for girls who are also least likely to self-select into violence. Nonetheless, in this section, we show that our results are robust to any potential selection concerns by employing propensity score matching difference-in-differences (PSM-DID)[40]. To this end, we first match the treated and the control groups on several observable characteristics such as the age, gender and grade of the child and household size using the nearest neighbor matching[41]and later estimate the effect of conflict on reading and math test scores using the matched sample of students only. Appendix Table A.13 shows the balance test before and after matching. The treated and the control groups are similar on observable characteristics

[37]We standardize this total test score by subtracting the mean of any given year and dividing by the standard deviation of the same year from each observation such that the mean and standard deviation in each year is 0 and 1, respectively.

[38]Since ASER data only surveys the rural sample of children, our results should not be biased by the negative effect of insurgency on test scores.

[39]The negative effect of war on educational attainment was found for military families only, due to psychological stress. However, the educational attainment of civilian families was not impacted. Since ours is the sample of children largely from civilian families, exposure to war of 1999 should not potentially bias our results.

[40]Remember that we dropped those districts for which the parallel trends assumption was not satisfied and retained only those districts for which the assumption held. In this process, we may plausibly be choosing a selected sample of control districts which are systematically different than our treated districts. Consequently, we may be running into endogeneity issues. Although, in Section 4, we provide evidence against any endogeneity concerns, we still proceed with the PSM-DID to alleviate any remaining potential concerns of endogeneity.

[41]We choose two nearest neighbors so as to retain most of the sample and yet achieve balance on observable covariates.

after matching with no statistically significant differences in means. Table 14 shows that our main results are robust to any selection issues. The treatment effects are negative and remain statistically significant at the 1% level. In fact, on the contrary, the effect sizes increase in magnitude than our original estimates in Table 2.

[Table 14 about here]

Since we also use the IHDS datasets in some of our analyses, which only surveys in two of our four control districts, we could not test the parallel trends assumption because there was only one data point in the pre-conflict period[42]. As a further robustness check, we only retain two unaffected districts in Jammu region (Jammu and Rajauri) in the ASER data as comparison group and show that the parallel trends assumption holds in Figures 6c and 6d. We also estimate the effect of civil unrest on learning outcomes using this alternative identification strategy and present the results in Appendix Table A.9. The results in Table A.9 are in line with our main results in Table 2. We find negative and statistically significant effects across specifications for both the reading and math scores. Appendix Table A.10 presents the LPM results for each of the reading and math test score level. These results also corroborate with our findings in Table 13.

In section 4, we showed that the parallel trends assumption was violated if we use all the districts in Jammu and Ladakh regions as comparison group for the treated districts of Kashmir. In this section, we present the main results from estimating equation 1 using all the unaffected districts as control group (the results are presented in Appendix Table A.15) and test the sensitivity of our estimates to the violation of parallel trends by following Rambachan & Roth (2023). In their paper, Rambachan & Roth (2023) propose robust inference and sensitivity analysis methods for empirical settings where the parallel trends assumption may not be valid. They demonstrate that the causal parameter of interest can still be (partially) identified by imposing a broad range of restrictions that ensure the post-treatment deviations from parallel trends are not excessively divergent from the pre-treatment trends. In other words, rather than assuming exact parallel trends, they constrain the potential differences in trends after treatment based on the observed pre-treatment trends. In Figure 8, we present the sensitivity analysis results based on estimates obtained in Appendix Figure A.3. As can been seen in Appendix Figure A.3, there is a clear downward trend in test score outcomes. Figures 8a and 8b report results for the post unrest years 2011/12 by constructing the robust confidence intervals about how non-linear the differences in trends have to be so as to nullify the negative effect of unrest in 2011/12. In the red, we present the original DID confidence set for estimating equation 2 with full set of control districts. In blue, we present confidence sets for different values of M (M represents the maximum non-linearity between two consecutive periods). $M = 0$ allows for the linear violations of the parallel trends while strictly positive values of M allow for non-linearity. As Figures 8a and 8b show, the robust confidence interval, when we allow for the linear violation of the parallel trends (that is when $M = 0$), depicts larger negative and statistically significant effects of violence than our original OLS estimates — the upper and the lower values of the confidence sets are much greater in magnitude than the original. As we allow for non-linear violation of parallel trends (for values of $M > 0$), the robust confidence intervals become wider but remain statistically significant. The breakdown value for a significant effect is $M = 0.09$ for reading and $M = 0.10$ for maths. These higher values of M suggest that the violation of parallel trends in the post-unrest period (relative to the pre-unrest period) has to be very large so as to nullify the negative effects of unrest that we document in Appendix Table A.15.

[42]IHDS-1 was conducted in 2004/5, which is before the 2010 unrest and IHDS-2 was conducted just after the 2010 unrest in 2011/12.

8 Conclusion

In this paper, we study the microeconomic effects of exposure to civil unrest during school-going age on educational quality — as measured by student performance on national standardized reading and math tests. While the existing literature has provided evidence that violent conflicts negatively affect the quantity of education such as attainment, enrollment, attendance, etc., not many papers have studied the negative effects on quality of education. Moreover, few papers which have studied the effects on academic performance largely focus on very localized violence perpetrated by drug gangs, instances of police violence, and homicides. Yet, none of them study the negative effects of civil unrest — where people are exposed to shutdowns and are subjected to a round-the-clock curfews — which instill a pervasive sense of insecurity, fear, anxiety, and psychological stress. We attempt to fill this gap in the literature by focusing on the civil unrest of 2010 in Kashmir which resulted in the tragic loss of at least 112 lives — the majority of whom where students and young adults in their 20s — and which resulted in continuous curfews and shutdowns in Kashmir districts.

Using a difference-in-differences design, we find significant decline in educational quality resulting from exposure to civil unrest. Specifically, we document large reductions in both the reading and math test scores among students who have experienced such violence. These adverse effects persist for at least two academic years and are particularly pronounced among younger primary and middle school students. While we do not find any evidence of differential effects by gender, socioeconomic status and the type of school the child attends, our findings indicate that exposure to civil unrest affects test scores up to the median of the distribution. Additionally, although we find no evidence linking unrest to increased dropout rates, we do find some evidence of reduced school enrolment. Regarding plausible transmission mechanisms, we find no suggestive evidence of school closures or more generally the loss of instructional time (due to student absenteeism or school closures) as a channel explaining our main results. While we find (weak) evidence of reduced school quality as a mechanism, we find a strong suggestive evidence of psychological stress as an important channel linking unrest to test score outcomes. We carry a battery of robustness checks to show that our results are robust to alternative specifications, an alternative identification, test score measurements and selection into violence. Besides, we also show that our results are robust to the violation of parallel trends assumption.

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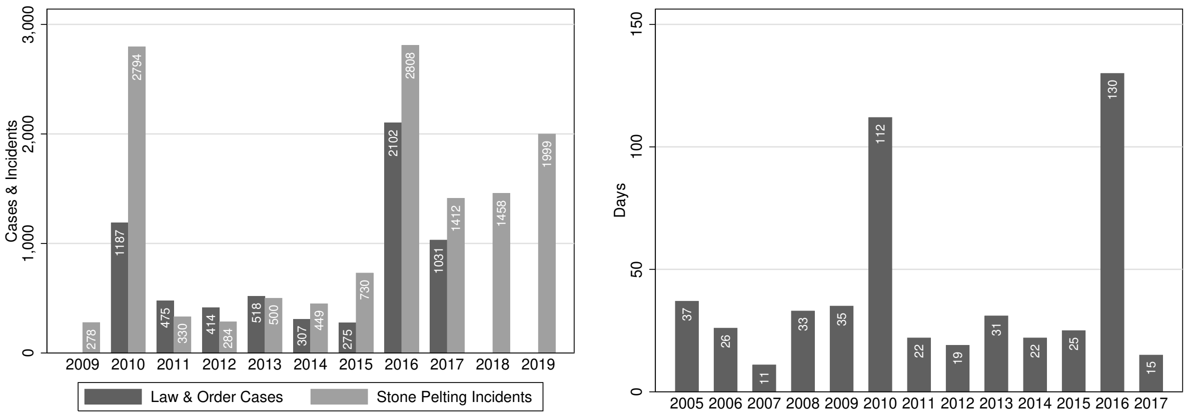
Figures

Figure 1: District Map of Indian Administrated Jammu and Kashmir

(a) State Regions (b) Treatment Status

Notes: This is the district map of the Indian Administrated Jammu and Kashmir. The Map is created using country level data from DIVA-GIS. For details, see https://diva-gis.org/gdata. Panel (a) shows the three distinct regions (divisions) of the state while panel (b) shows the treatment status of each district (see Section 4 for more details about panel (b).

Figure 2: Kashmir Conflict

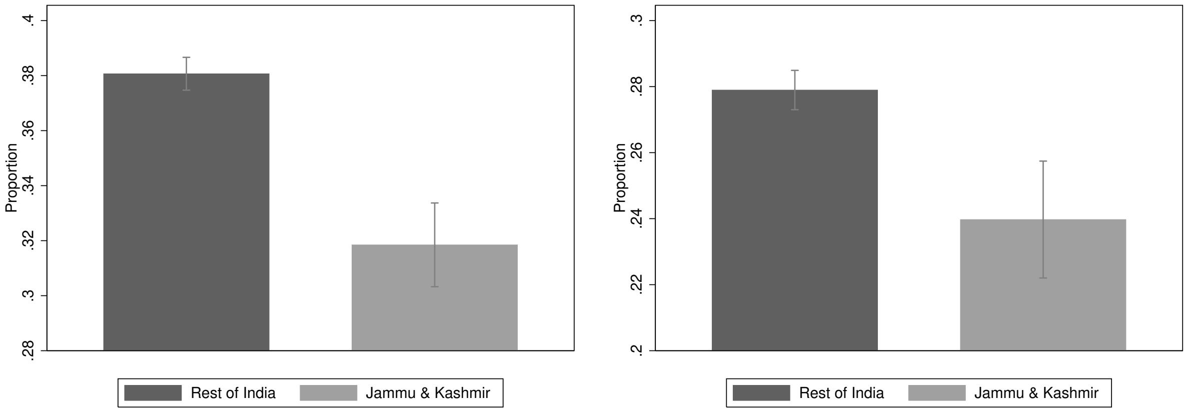


(a) Law and Order Cases and Stone Pelting Incidents

(b) Number of Working Days Affected

Notes: Panel (a) shows the number of law and order cases and stone pelting incidents recorded in Kashmir since 2009. Panel (b) shows the number of working days affected due to curfews, protest demonstrations and calls for a strike since 2005. *Data sources*: Law and order cases and working days affected are reported in Parvaiz (2017) and stone pelting incidents in Ganie (2021). Parvaiz (2017) presents official data shared by J&K police officials, the crime branch of J&K police and media reports. Ganie (2021) presents administrative data from Home Ministries of the country and the state.

Figure 3: Literacy and numeracy skills of students (in grades 1-12) in Jammu and Kashmir and the Rest of India

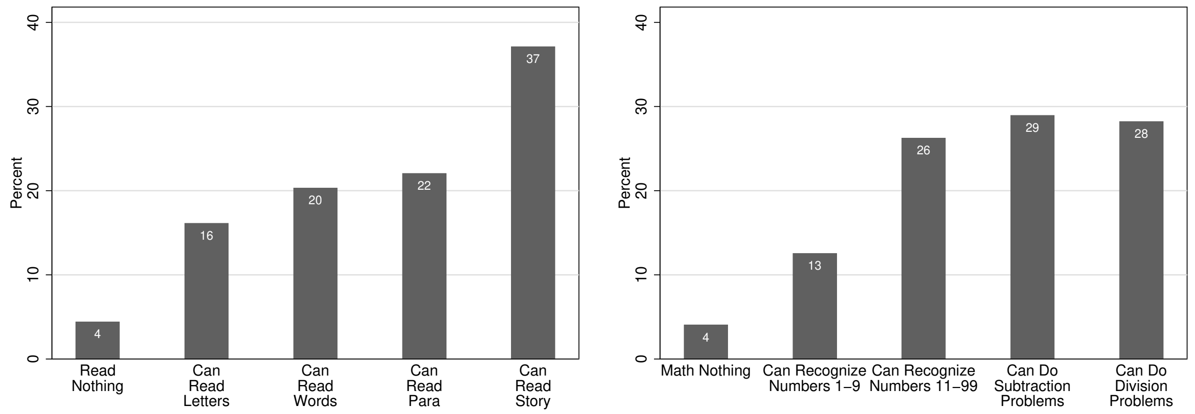


(a) Grade-II Textbook Level

(b) Grade-IV Level Arithmetic

Notes: Panels (a) and (b) respectively present the proportion of children in grades 1–12 who can comfortably read a short story (equivalent to a grade II textbook) and solve a division problem (equivalent to a grade IV textbook) in Jammu and Kashmir and the rest of Indian states. 95% confidence intervals are also reported (these are calculated using robust clustered standard errors at the district level). *Data sources:* ASER household surveys 2007-2012. The data for 2010 is not available for J&K.

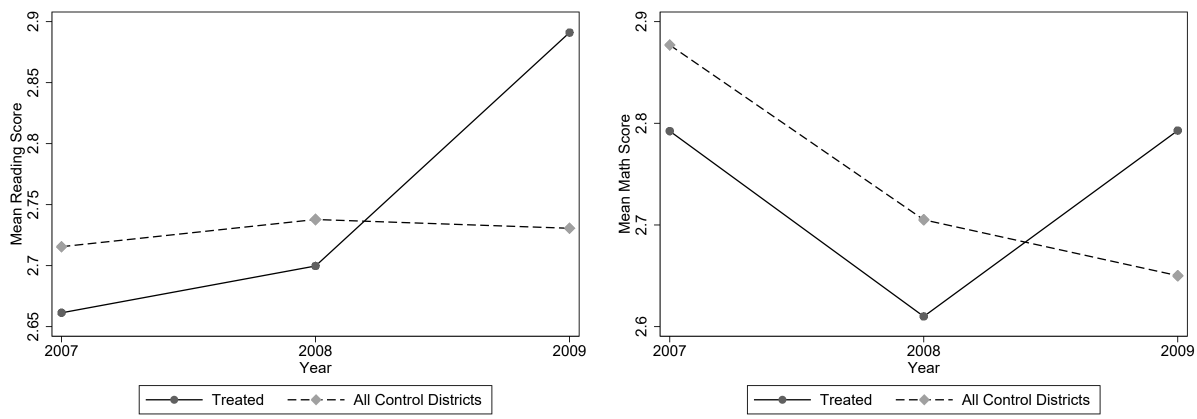
Figure 4: Distribution of learning outcome of students in Jammu and Kashmir



(a) Reading (b) Mathematics

Notes: Panels (a) and (b) respectively show the percentage of children (in grades 1–12) who can comfortably read at different levels of mastery and solve math problem at various levels of mastery in the state Jammu and Kashmir. *Data sources:* ASER household surveys 2007-2012. The data for 2010 is not available for J&K.

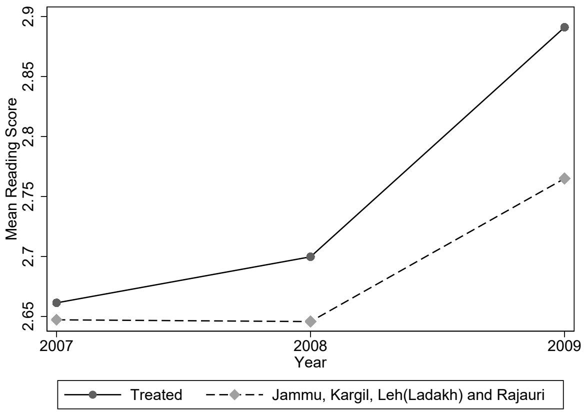
Figure 5: Parallel trends: All control districts



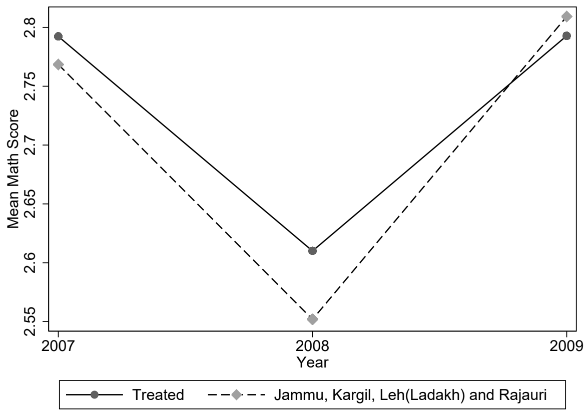
(a) Reading (b) Mathematics

Notes: Panels (a) and (b) plot the raw means of the reading score and the math score for the children in the treated and the control districts in the pre-unrest period, respectively. The *treatment* group comprises all children in all of the districts of Kashmir, while the *control* group comprises all children in all of the districts of Jammu and Ladakh regions. *Data sources:* ASER household surveys 2007-2009.

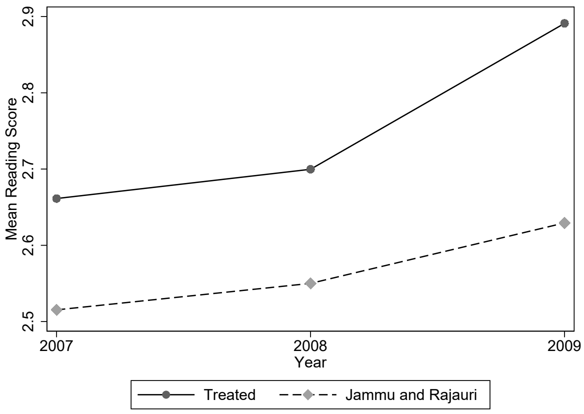
Figure 6: Parallel trends: Some control districts



(a) Reading



(b) Mathematics

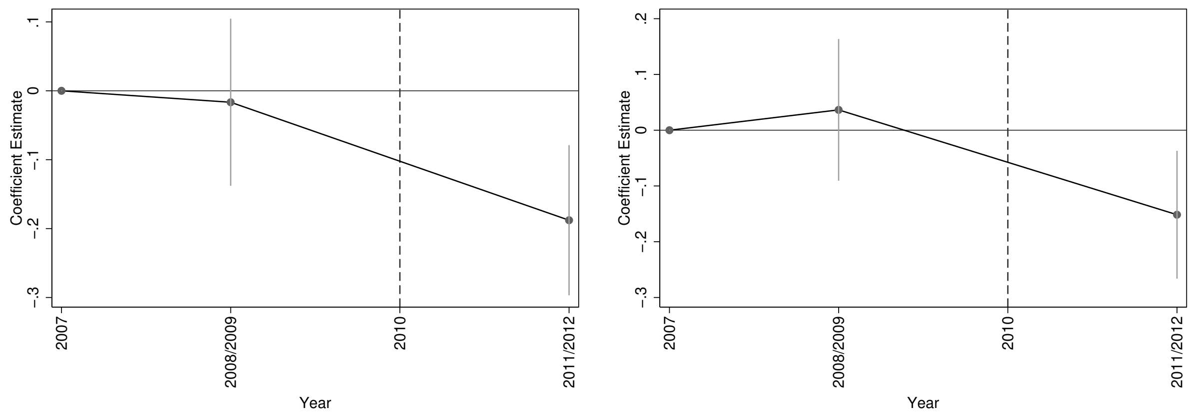


(c) Reading

(d) Mathematics

Notes: Panels (a), (c) and (b), (d) plot the raw means of the reading score and the math score for the children in the treated and the control districts in the pre-unrest period, respectively. In panels (a) and (b), the *treatment* group comprises all children in all of the districts of Kashmir, while the *control* group comprises all children in some of the districts of Jammu (Jammu and Rajauri) and Ladakh (Leh(Ladakh) and Kargil) regions. In panels (c) and (d), the *treatment* group comprises all children in all of the districts of Kashmir, while the *control* group comprises all children in some of the districts of Jammu (Jammu and Rajauri) region.*Data sources:* ASER household surveys 2007-2009.

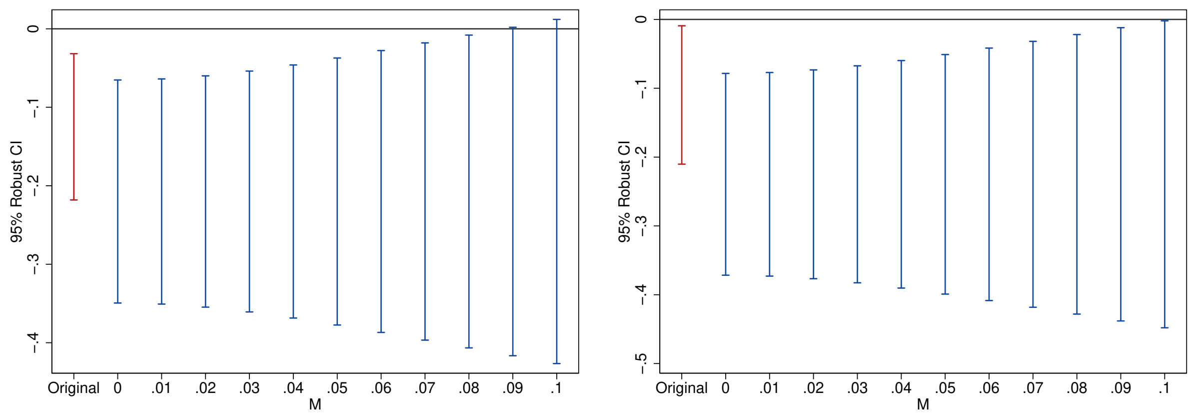
Figure 7: Civil unrest and yearly learning outcomes: Event study estimates



(a) Reading (b) Mathematics

Notes: The figure shows the effect of civil unrest by two-year bands; the dependent variables in panels (a) and (b) are the standardized reading and math scores, respectively; the estimated coefficients are presented from estimating equation 2; the connected solid line refers to the coefficient estimates on the difference-in-differences interaction term in specification 2; the coefficient estimate for 2007 is normalized to zero (base year); the 95% confidence intervals are shown by the vertical bars around the coefficient estimates; the *treatment* indicator takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); regressions control for child's gender and grade and household size; data source is ASER household surveys 2007-2012, excluding 2010.

Figure 8: Sensitivity analysis using smoothness restrictions: Allowing for the violation of Parallel Trends



(a) Reading (b) Mathematics

Notes: Panels (a) and (b) show sensitivity analyses of estimated treatment effects of civil unrest on (standardized) reading and math scores, respectively, to the violations of the parallel trends assumptions based on the recommendation of Rambachan & Roth (2023). In each panel, the red bar represents the original 95% confidence interval of the difference-in-differences (DID) estimate obtained by estimating equation 2 with full set of control districts (i.e., all districts of Jammu and Ladakh region are taken as a control group). The blue bars present the corresponding 95% robust confidence intervals when we allow parallel trends to deviate up to M times per period. M denotes the maximum permissible deviation in the slope of an underlying (pre) trend between two consecutive periods. For more details, see Rambachan & Roth (2023).

Tables

Table 1: Summary statistics

	Mean	SD	Min	Max	N
Can Read Letters	0.802	0.398	0	1	80,989
Can Read Words	0.667	0.471	0	1	80,989
Can Read Para	0.497	0.500	0	1	80,989
Can Read Story	0.311	0.463	0	1	80,989
Reading Score	2.713	1.238	0	4	67,986
Can Recognize Numbers 1-9	0.798	0.402	0	1	80,989
Can Recognize Numbers 11-99	0.694	0.461	0	1	80,989
Can Do Subtraction Problems	0.475	0.499	0	1	80,989
Can Do Division Problems	0.235	0.424	0	1	80,989
Math Score	2.648	1.134	0	4	67,347
Enrollment	0.967	0.179	0	1	80,989
Grade	5.413	2.973	1	14	62,982
Age	10.187	3.708	3	16	80,636
Gender (1=Male)	0.540	0.498	0	1	79,883
Mother's Age	35.393	6.645	17	80	76,474
Father's Age	39.833	7.568	18	85	40,511
Literate Mother	0.391	0.488	0	1	77,990
HH Size	7.297	3.047	1	25	80,989

Data Source: ASER household surveys 2007-2012. The data for 2010 is not available for J&K.

Table 2: The effect of civil unrest on learning outcomes

	Standardized Reading Score				Standardized Math Score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Kashmir x Post	-0.070	-0.090**	-0.516***	-0.543***	-0.122**	-0.143***	-0.366***	-0.369***
	(0.047)	(0.042)	(0.113)	(0.116)	(0.049)	(0.045)	(0.119)	(0.118)
Controls	No	No	No	Yes	No	No	No	Yes
Observations	46,770	46,596	46,596	40,736	46,409	46,242	46,242	40,466
R-Squared	0.004	0.454	0.459	0.436	0.004	0.424	0.429	0.412
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
District-specific Trends	No	No	Yes	Yes	No	No	Yes	Yes

Note: The dependent variables, standardized reading and math scores, are standardized by year such that the mean and standard deviation in any given year is 0 and 1, respectively; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for years $2011-2012$ and 0 for years $2007-2009$; controls include child's age, gender and grade and household size; robust standard errors in parentheses are clustered at the village (PSU) level. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table 3: The effect of civil unrest on learning outcomes: Persistence

	Standardized Reading Score			Standardized Math Score		
	(1)	(2)	(3)	(4)	(5)	(6)
Kashmir x Post	-0.543***			-0.369***		
	(0.116)			(0.118)		
Kashmir x Post1		-0.513***	-0.543***		-0.359***	-0.361***
		(0.114)	(0.118)		(0.121)	(0.119)
Kashmir x Post2		-0.495***	-0.541***		-0.316**	-0.311**
		(0.144)	(0.149)		(0.154)	(0.153)
Controls	Yes	No	Yes	Yes	No	Yes
Observations	40,736	46,596	40,736	40,466	46,242	40,466
R-Squared	0.436	0.459	0.436	0.412	0.429	0.412
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
District-specific Trends	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variables, standardized reading and math scores, are standardized by year such that the mean and standard deviation in any given year is 0 and 1, respectively; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for years $2011 - 2012$ and 0 for years $2007 - 2009$; *Post*1 is an indicator that takes value 1 for year 2011 and 0 otherwise; *Post*2 is an indicator that takes value 1 for year 2012 and 0 otherwise; controls include child's age, gender and grade and household size; robust standard errors in parentheses are clustered at the village (PSU) level. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table 4: Heterogenous effect of civil unrest on learning outcomes: Grades

	Standardized Reading Score			Standardized Math Score		
	(1) Primary	(2) Middle	(3) Secondary	(4) Primary	(5) Middle	(6) Secondary
Kashmir x Post	-0.505***	-0.659***	-0.346***	-0.224	-0.577***	-0.363***
	(0.145)	(0.160)	(0.097)	(0.141)	(0.162)	(0.106)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,359	11,581	7,684	21,189	11,513	7,654
R-Squared	0.291	0.072	0.078	0.297	0.067	0.084
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
District-specific Trends	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variables, standardized reading and math scores, are standardized by year such that the mean and standard deviation in any given year is 0 and 1, respectively; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for years $2011 - 2012$ and 0 for years $2007 - 2009$; *Primary*, *Middle* and *Secondary* comprise children in grades $1 - 5$, $6 - 8$ and $9 - 12$, respectively; controls include child's age, gender and grade and household size; robust standard errors in parentheses are clustered at the village (PSU) level. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table 5: Heterogenous effect of civil unrest on learning outcomes: Gender, socioeconomic status and type of school

	Standardized Reading Score			Standardized Math Score		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Gender	(Male)	(Female)	(DDD)	(Male)	(Female)	(DDD)
Kashmir x Post	-0.579***	-0.509***	-0.535***	-0.386***	-0.353***	-0.363***
	(0.118)	(0.128)	(0.117)	(0.118)	(0.131)	(0.119)
Kashmir x Post x Male			-0.009			-0.004
			(0.030)			(0.031)
Observations	21,659	19,077	40,736	21,498	18,968	40,466
R-Squared	0.443	0.430	0.436	0.425	0.399	0.412
Panel B: Type of dwelling	(Pucca)	(Kutcha)	(DDD)	(Pucca)	(Kutcha)	(DDD)
Kashmir x Post	-0.808***	-0.515***	-0.625***	-0.627***	-0.288	-0.391**
	(0.158)	(0.173)	(0.145)	(0.177)	(0.179)	(0.152)
Kashmir x Post x Pucca			0.055			0.007
			(0.068)			(0.074)
Observations	12,883	19,995	32,878	12,812	19,863	32,675
R-Squared	0.426	0.482	0.464	0.388	0.446	0.430
Panel B: Type of school	(Private)	(Public)	(DDD)	(Private)	(Public)	(DDD)
Kashmir x Post	-0.458***	-0.536***	-0.533***	-0.239*	-0.375***	-0.346***
	(0.143)	(0.126)	(0.113)	(0.139)	(0.131)	(0.116)
Kashmir x Post x Private			0.095			0.056
			(0.063)			(0.064)
Observations	14,696	25,602	40,298	14,602	25,430	40,032
R-Squared	0.417	0.509	0.477	0.405	0.471	0.450
Controls	Yes	Yes	Yes	Yes	Yes	Yes
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
District-specific Trends	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variables, standardized reading and math scores, are standardized by year such that the mean and standard deviation in any given year is 0 and 1, respectively; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for years $2011-2012$ and 0 for years $2007-2009$; *Pucca* refers to children who reside in houses made of concrete materials, while *Kutcha* refers to children who reside in houses made of mud; controls include child's age, gender and grade and household size; robust standard errors in parentheses are clustered at the village (PSU) level. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table 6: Distributional effects of civil unrest on learning outcomes: Quantile Regression

	OLS	Quantile Regression				
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	10th	25th	50th	75th	90th
Panel A: Standardized Reading Score						
Kashmir x Post	-0.543***	-0.620***	-0.601***	-0.052**	0.000**	-0.000
	(0.116)	(0.075)	(0.067)	(0.021)	(0.000)	(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,736	40,736	40,736	40,736	40,736	40,736
Panel B: Standardized Math Score						
Kashmir x Post	-0.369***	-0.333***	-0.383***	-0.058**	-0.024***	-0.000***
	(0.118)	(0.093)	(0.130)	(0.026)	(0.009)	(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,466	40,466	40,466	40,466	40,466	40,466
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
District-specific Trends	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variables, standardized reading and math scores, are standardized by year such that the mean and standard deviation in any given year is 0 and 1, respectively; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for years $2011-2012$ and 0 for years $2007-2009$; controls include child's age, gender and grade and household size; robust standard errors in parentheses are clustered at the village (PSU) level for OLS estimates in column 1 and bootstrapped using between-quantile blocks in columns 2-6; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table 7: Effect of civil unrest on school enrolment

	School enrolment					
	(1)	(2)	(3)	(4)	(5)	(6)
Kashmir	-0.011***	-0.010***				
	(0.003)	(0.003)				
Post	0.002	0.003	0.003			
	(0.002)	(0.002)	(0.002)			
Kashmir x Post	0.004	0.003	0.003	0.003	0.003	-0.023**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.010)
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	57,358	56,577	56,577	56,577	56,577	56,577
R-Squared	0.002	0.004	0.006	0.007	0.008	0.010
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
District-specific Trends	No	No	No	No	No	Yes

Note: The dependent variable, school enrolment, is an indicator taking value 1 for children who are currently enrolled in school and 0 for never enrolled children; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for years $2011-2012$ and 0 for years $2007-2009$; controls include child's age, gender and household size; robust standard errors in parentheses are clustered at the village (PSU) level; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table 8: Effect of civil unrest on drop-out rates

	Probability of dropping out of school					
	(1)	(2)	(3)	(4)	(5)	(6)
Kashmir	0.016***	0.012***				
	(0.002)	(0.002)				
Post	0.003	0.002	0.002			
	(0.002)	(0.002)	(0.002)			
Kashmir x Post	0.001	0.001	0.001	0.002	0.003	0.007
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)
Controls	No	Yes	Yes	Yes	Yes	Yes
Observations	57,358	56,577	56,577	56,577	56,577	56,577
R-Squared	0.004	0.029	0.030	0.032	0.040	0.042
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
District-specific Trends	No	No	No	No	No	Yes

Note: The dependent variable is an indicator taking value 1 for children who have dropped-out of school and 0 otherwise; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for years $2011-2012$ and 0 for years $2007-2009$; controls include child's age, gender and household size; robust standard errors in parentheses are clustered at the village (PSU) level; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table 9: Effect of civil unrest on performance of out-of-school children: School closures as an underlying mechanism

	Standardized Reading Score			Standardized Math Score		
	(1)	(2)	(3)	(4)	(5)	(6)
Kashmir x Post	-0.272	-0.861	-1.012	-0.623**	-0.679	-0.834
	(0.235)	(0.645)	(0.639)	(0.248)	(0.718)	(0.707)
Controls	No	No	Yes	No	No	Yes
Observations	967	967	962	951	951	946
R-Squared	0.241	0.257	0.264	0.228	0.249	0.263
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
District-specific Trends	No	Yes	Yes	No	Yes	Yes

Note: The dependent variables, standardized reading and math scores, are standardized by year such that the mean and standard deviation in any given year is 0 and 1, respectively; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for years $2011-2012$ and 0 for years $2007-2009$; controls include child's gender and household size; estimation sample is restricted to children who are out-of-school (either never enrolled or drop-out); robust standard errors in parentheses are clustered at the village (PSU) level; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table 10: Differential effect of civil unrest on performance of children by mother's education: Loss of instruction as an underlying mechanism

	Standardized Reading Score			Standardized Math Score		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Literate Mother	Literate Mother	Illiterate Mother	DDD	Literate Mother	Illiterate Mother	DDD
Kashmir x Post	-0.382**	-0.483***	-0.475***	-0.320**	-0.230	-0.306**
	(0.156)	(0.138)	(0.117)	(0.151)	(0.146)	(0.119)
Kashmir x Post x Literate Mother			0.087			0.098
			(0.066)			(0.073)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,592	25,881	39,473	13,518	25,705	39,223
R-Squared	0.440	0.456	0.447	0.439	0.420	0.423
Panel B: Educated Mother	Educated Mother	Uneducated Mother	DDD	Educated Mother	Uneducated Mother	DDD
Kashmir x Post	-0.340**	-0.526***	-0.480***	-0.317**	-0.302**	-0.290**
	(0.157)	(0.124)	(0.114)	(0.161)	(0.130)	(0.117)
Kashmir x Post x Educated Mother			0.075			0.026
			(0.062)			(0.071)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,605	31,131	40,736	9,552	30,914	40,466
R-Squared	0.451	0.448	0.445	0.457	0.415	0.422
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
District-specific Trends	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variables, standardized reading and math scores, are standardized by year such that the mean and standard deviation in any given year is 0 and 1, respectively; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for years $2011 - 2012$ and 0 for years $2007 - 2009$; controls include child's gender and grade and household size; *Literate & Illiterate mothers* refer to a sample of children whose mothers have went to school or not, respectively and *Educated & Uneducated mothers* refer to a sample of children whose mothers have more than or less than primary schooling, respectively; robust standard errors in parentheses are clustered at the village (PSU) level; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table 11: Confidence in schools to deliver quality education: Quality of schooling as an underlying mechanism

Dependent variable: Great confidence vs some confidence in schools to deliver quality education							
	Full Sample					Urban	Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Kashmir	0.221***						
	(0.057)						
Post	0.429***						
	(0.101)						
Kashmir x Post	-0.250**	-0.225**	-0.179*	-0.176*	-0.220*	0.020	-0.233*
	(0.077)	(0.074)	(0.079)	(0.080)	(0.097)	(0.136)	(0.109)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N Households	1253	1253	1221	1221	1221	497	724
R-Squared	0.122	0.155	0.159	0.160	0.173	0.193	0.165
District FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Caste FE	No	No	Yes	Yes	Yes	Yes	Yes
Religion FE	No	No	No	Yes	Yes	Yes	Yes
District-specific Trends	No	No	No	No	Yes	Yes	Yes

Note: The dependent variable is an indicator that takes value 1 if households report having *great confidence in schools to provide good education* and 0 if they report having *only some confidence*; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for IHDS-2 wave $(2011 - 2012)$ and 0 for IHDS-1 wave $(2004 - 2005)$; controls include household assets, highest education of adult household member, log household income and consumption expenditure and urban dummy; robust standard errors in parentheses are clustered at the PSU level; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is the IHDS-1 and IHDS-2 household surveys.

Table 12: Effect of civil unrest on private tuition (extensive margin effect): Psychological stress as an underlying mechanism

	Probability of availing paid private tuition			
	(1)	(2)	(3)	(4)
Kashmir x Post	-0.166***	-0.178***	-0.062	-0.050
	(0.043)	(0.043)	(0.078)	(0.081)
Controls	No	No	No	Yes
Observations	22,251	22,191	22,191	19,948
R-Squared	0.050	0.079	0.094	0.092
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Birth-Year FE	No	Yes	Yes	Yes
District-specific Trends	No	No	Yes	Yes

Note: The dependent variable is an indicator that takes value 1 if the child is currently availing paid private tuition and 0 otherwise; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for years $2011-2012$ and 0 for years $2007-2009$; controls include child's gender and grade and household size; robust standard errors in parentheses are clustered at the village (PSU) level; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table 13: Effect of civil unrest on learning outcomes using alternative specification: Linear probability model estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Child can read				Child can recognize or solve			
	Letter	Word	Paragraph	Story	Digits 1-9	Digits 10-99	Subtraction	Division
Kashmir x Post	-0.020	-0.094**	-0.219***	-0.232***	-0.040	-0.052	-0.157***	-0.153***
	(0.032)	(0.043)	(0.053)	(0.058)	(0.038)	(0.046)	(0.053)	(0.055)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43,938	43,938	43,938	43,938	43,938	43,938	43,938	43,938
R-Squared	0.080	0.178	0.294	0.297	0.070	0.145	0.282	0.271
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-specific Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each of the dependent variable is an indicator that takes value 1 if the child can read or solve at the level given by the model label and 0 otherwise; all models are estimated using linear probability models; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for years $2011-2012$ and 0 for years $2007-2009$; controls include child's gender and grade and household size; robust standard errors in parentheses are clustered at the village (PSU) level; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table 14: Effect of civil unrest on learning outcomes: Propensity score matching difference-in-differences

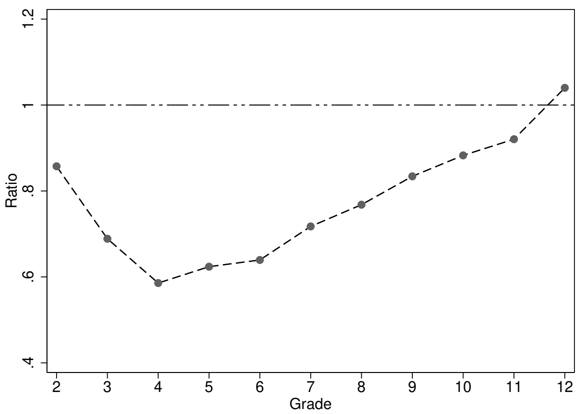
	Standardized Reading Score			Standardized Math Score		
	(1)	(2)	(3)	(4)	(5)	(6)
Kashmir x Post	-0.579***	-0.696***	-0.782***	-0.515**	-0.643***	-0.709***
	(0.211)	(0.205)	(0.230)	(0.208)	(0.203)	(0.228)
Controls	No	Yes	Yes	No	Yes	Yes
Additional Controls	No	No	Yes	No	No	Yes
Observations	28,602	28,602	6,907	28,461	28,461	6,870
R-Squared	0.426	0.440	0.490	0.431	0.446	0.500
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
District-Specific Trends	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variables, standardized reading and math scores, are standardized by year such that the mean and standard deviation in any given year is 0 and 1, respectively; $Kashmir$ is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for years $2011-2012$ and 0 for years $2007-2009$; controls include child's gender and grade and household size; estimation sample is restricted to the matched sample from nearest neighbor matching ($n=2$) with common support; all regressions are weighted using PSM weights; robust standard errors in parentheses are clustered at the village (PSU) level; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

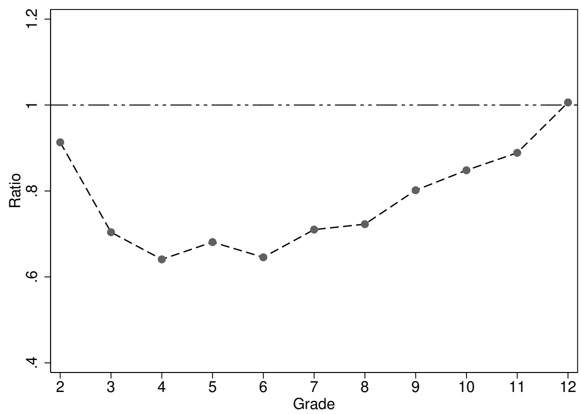
9 Appendix A

Figures

Figure A.1: Grade-wise Literacy and numeracy skills of students of Jammu and Kashmir relative to the Rest of India



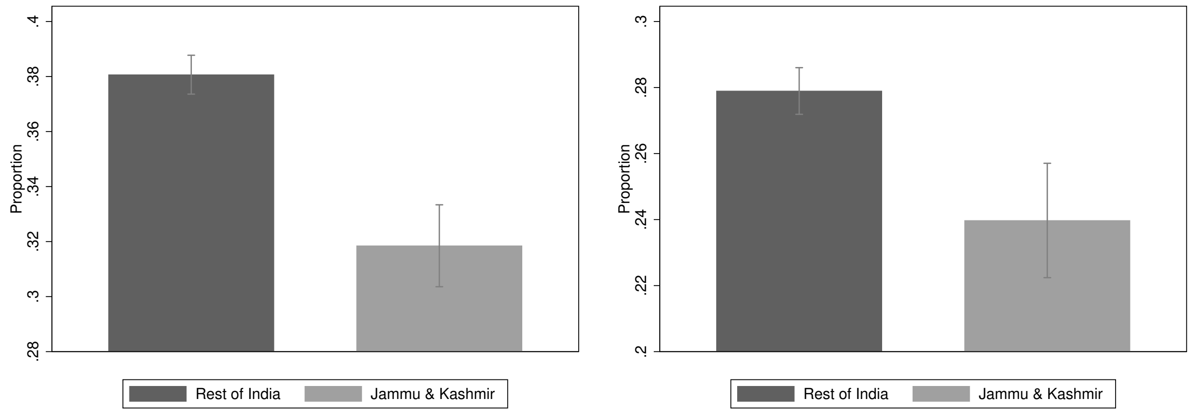
(a) Grade-II textbook



(b) Grade-IV Arithmetic

Notes: Panels (a) and (b) plot the grade-wise disparities in reading and math proficiency for children of Jammu and Kashmir relative to the rest of India, respectively. 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. *Data source:* ASER household surveys 2007-2012, excluding 2010 for which the data is not available for J&K.

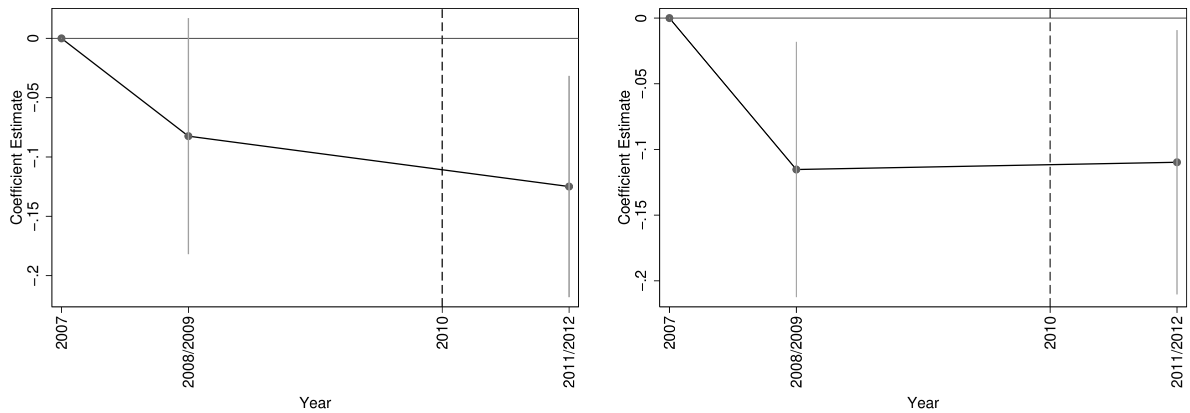
Figure A.2: Grade-wise Literacy and numeracy skills of students of Jammu and Kashmir relative to the Rest of India: By gender



(a) Grade-II textbook (b) Grade-IV Arithmetic

Notes: This figure plots the gender-wise relative disparities in learning outcomes between children of Jammu and Kashmir and the rest of India. Refer to Figure A.5 for more details. *Data source:* ASER household surveys 2007-2012, excluding 2010 for which the data is not available for J&K.

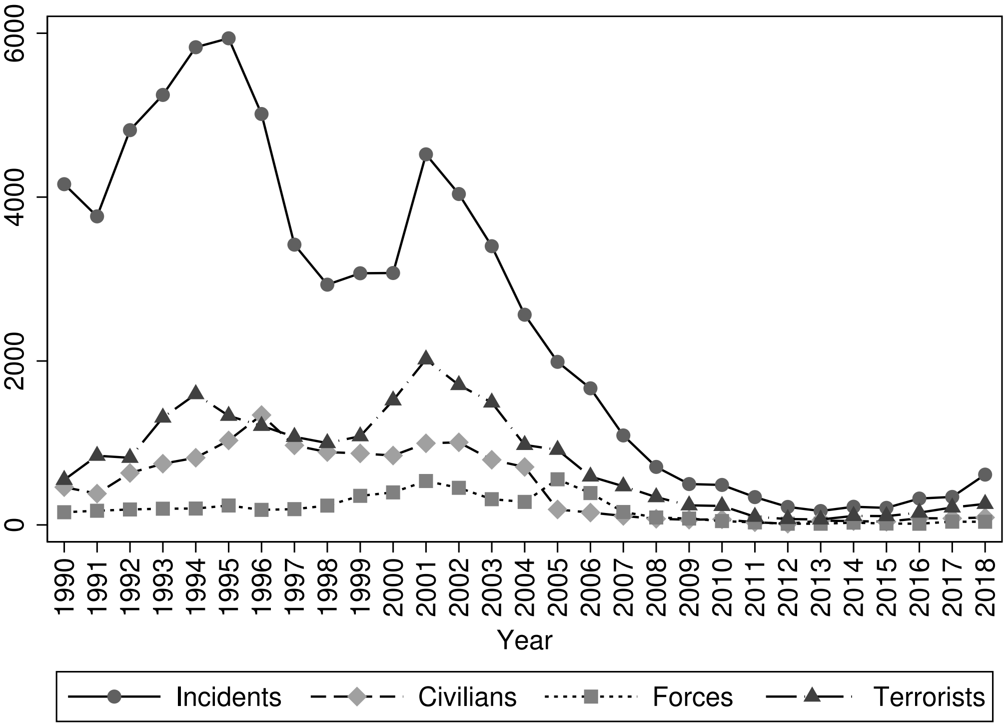
Figure A.3: Civil unrest and yearly learning outcomes: Event study estimates with full set of control districts



(a) Reading (b) Mathematics

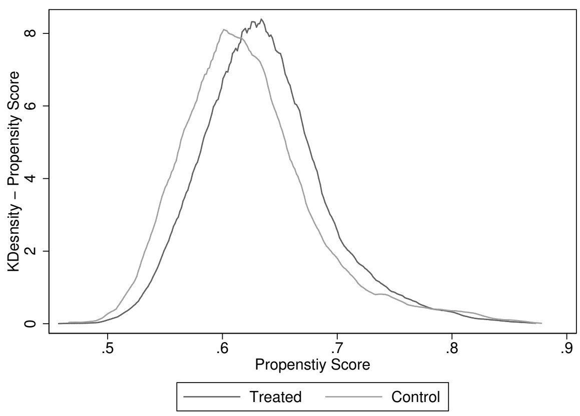
Notes: The figure shows the effect of civil unrest by two-year bands; the dependent variables in panels (a) and (b) are the standardized reading and math scores, respectively; the estimated coefficients are presented from estimating equation 2; the connected solid line refers to the coefficient estimates on the difference-in-differences interaction term in specification 2; the coefficient estimate for 2007 is normalized to zero (base year); the 95% confidence intervals are shown by the vertical bars around the coefficient estimates; the *treatment* indicator takes value 1 for the children in districts of Kashmir and 0 for children in all districts of Jammu and Ladakh regions; regressions control for child's gender and grade and household size; data source is ASER household surveys 2007-2012, excluding 2010.

Figure A.4: Kashmir Insurgency: Number of insurgency related incidents and associated fatalities

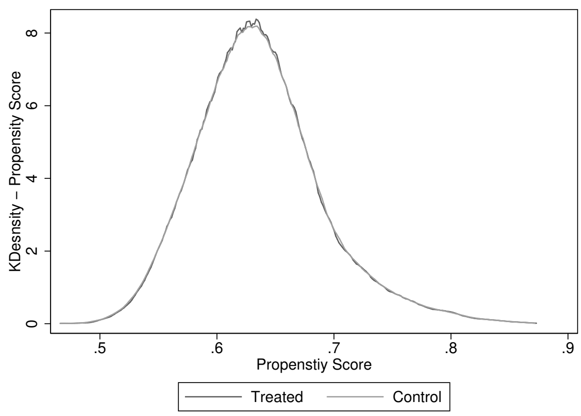


Notes: The figure presents the number of insurgency related incidents and associated killings of civilians, security forces and terrorists in the state of Jammu and Kashmir from 1990-2018. *Data source:* Several annual reports of the Ministry of Home Affairs, Government of India. For reference, see the annual report of 2010, Ministry of Home Affairs (2010)

Figure A.5: The Density of Propensity Scores Before and After Matching

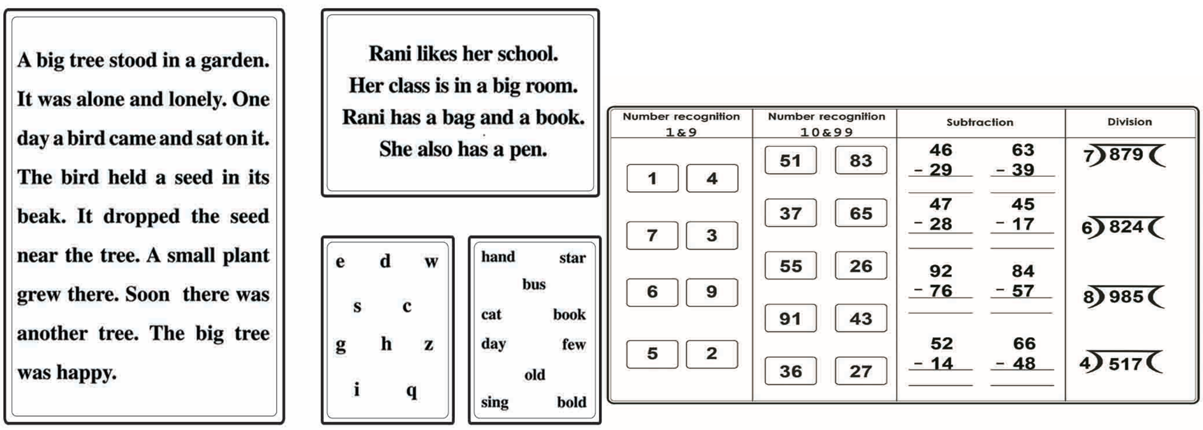


(a) Before Matching



(b) After Matching

Figure A.6: ASER testing tools



(a) Reading Module

(b) Math Module

Notes: Figure shows the ASER testing tools in English language. Panel (a) shows the reading test module with four components — letters, words, paragraph and a short story. Panel (b) shows the math test module with four components — recognition of single-digit numbers and double-digit numbers, subtraction (with borrowing) and division problems (three-digit by one-digit).

Tables

Table A.1: Falsification Test: Parallel Trends

	Standardized Reading Score		Standardized Math Score	
	(1)	(2)	(3)	(4)
Kashmir x PseudoPost	0.066	0.069	-0.064	-0.062
	(0.119)	(0.120)	(0.127)	(0.127)
Controls	Yes	Yes	Yes	Yes
Observations	26,032	26,032	25,810	25,810
R-Squared	0.467	0.485	0.452	0.470
District FE	Yes	Yes	Yes	Yes
District-specific Trends	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Birth-Year FE	No	Yes	No	Yes

Note: The dependent variables, standardized reading and math scores, are standardized by year such that the mean and standard deviation in any given year is 0 and 1, respectively; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *PseudoPost* is an indicator that takes value 1 for year 2009 and 0 for years 2007 and 2008; The estimation sample of children is restricted till 2009; controls include child's age, gender and grade and household size; robust standard errors in parentheses are clustered at the village (PSU) level. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2009.

Table A.2: Pre-unrest characteristics and exposure at the district level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ASER		IHDS-1 (2004/5)						
	Reading	Math	Average confidence in					Avg per-capita	Percentage of
	Score	Score	Government	Politicians	Police	Schools	Courts	expenditure	poor
Kashmir	0.052	0.020	0.440**	0.121	0.250	-0.014	0.177	-260.493	0.036
	(0.073)	(0.063)	(0.130)	(0.140)	(0.138)	(0.085)	(0.161)	(219.121)	(0.018)
Districts	10	10	5	5	5	5	5	5	5
R-Squared	0.060	0.013	0.793	0.201	0.523	0.009	0.286	0.320	0.575

Note: The dependent variables in columns 1 and 2 are mean reading and math test scores at the district level, respectively; the dependent variables in columns 3-7 are the average confidence at the district level in state government, politicians, police, schools and courts, respectively; the dependent variables in columns 8 and 9 are the average per-capita consumption expenditure and percentage of poor households at the district level, respectively; *Kashmir* is an indicator that takes value 1 for households in districts of Kashmir and 0 for households in districts Jammu and Rajauri; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010 for columns 1 and 2 and the IHDS-1 (2004/05) for the rest of the columns.

Table A.3: Effect of civil unrest of learning outcomes: Additional control variables

	Standardized Reading Score			Standardized Math Score		
	(1)	(2)	(3)	(4)	(5)	(6)
Kashmir x Post	-0.516***	-0.543***	-0.472***	-0.366***	-0.369***	-0.307***
	(0.113)	(0.116)	(0.117)	(0.119)	(0.118)	(0.118)
Controls	No	Yes	Yes	No	Yes	Yes
Additional Controls	No	No	Yes	No	No	Yes
Observations	46,596	40,736	38,565	46,242	40,466	38,329
R-Squared	0.459	0.436	0.447	0.429	0.412	0.423
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
District-specific Trends	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variables, standardized reading and math scores, are standardized by year such that the mean and standard deviation in any given year is 0 and 1, respectively; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for years $2011-2012$ and 0 for years $2007-2009$; controls include child's gender and grade and household size; additional controls include mother's age, an indicator for whether or not she went to school and an indicator for whether or not she has more than primary education; robust standard errors in parentheses are clustered at the village (PSU) level. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table A.4: Heterogeneous effect of civil unrest by grades: Falsification test

	Standardized Reading Score			Standardized Math Score		
	(1) Primary	(2) Middle	(3) Secondary	(4) Primary	(5) Middle	(6) Secondary
Kashmir x Pseudo Post	0.091	0.193	-0.069	-0.116	0.091	-0.194
	(0.145)	(0.150)	(0.131)	(0.146)	(0.162)	(0.138)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,918	7,237	4,764	13,786	7,179	4,734
R-Squared	0.314	0.108	0.094	0.321	0.102	0.097
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
District-specific Trends	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variables, standardized reading and math scores, are standardized by year such that the mean and standard deviation in any given year is 0 and 1, respectively; $Kashmir$ is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); $PseudoPost$ is an indicator that takes value 1 for year 2009 and 0 for years 2007 and 2008; The estimation sample of children is restricted till 2009; $Primary$, $Middle$ and $Secondary$ comprise children in grades $1-5$, $6-8$ and $9-12$, respectively; controls include child's gender and grade and household size; robust standard errors in parentheses are clustered at the village (PSU) level. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2009.

Table A.5: Heterogeneous effect of civil unrest by gender, socioeconomic status and type of school: Falsification test

	(1) Male	(2) Female	(3) Pucca	(4) Kutcha	(5) Private	(6) Government
Panel A: Standardized Reading Score						
Kashmir x Pseudo Post	0.077	0.055	0.969	0.574	0.023	0.059
	(0.123)	(0.132)	(5.963)	(15.557)	(0.137)	(0.130)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,330	11,702	6,211	12,101	8,752	17,019
R-Squared	0.492	0.481	0.547	0.539	0.494	0.526
Panel B: Standardized Math Score						
Kashmir x Pseudo Post	-0.049	-0.085	1.944	0.104	-0.028	-0.113
	(0.128)	(0.143)	(5.269)	(17.005)	(0.152)	(0.145)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,197	11,613	6,149	12,007	8,685	16,866
R-Squared	0.483	0.457	0.490	0.511	0.462	0.510
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
District-specific Trends	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variables, standardized reading and math scores, are standardized by year such that the mean and standard deviation in any given year is 0 and 1, respectively; $Kashmir$ is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); $PseudoPost$ is an indicator that takes value 1 for year 2009 and 0 for years 2007 and 2008; The estimation sample of children is restricted till 2009; $Pucca$ refers to children who reside in houses made of concrete materials, while $Kutcha$ refers to children who reside in houses made of mud; controls include child's gender and grade and household size; robust standard errors in parentheses are clustered at the village (PSU) level. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2009.

Table A.6: Confidence in schools to deliver quality education : School Quality

Dependent variable: Great confidence vs no confidence in schools to deliver quality education							
	Full Sample					Urban	Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Kashmir	0.032						
	(0.048)						
Post	0.015						
	(0.076)						
Kashmir x Post	-0.020	-0.008	-0.022	-0.027	-0.107	0.177	-0.046
	(0.054)	(0.055)	(0.064)	(0.065)	(0.075)	(0.110)	(0.096)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N Households	917	917	892	892	892	337	555
R-Squared	0.067	0.088	0.094	0.097	0.133	0.242	0.063
District FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Caste FE	No	No	Yes	Yes	Yes	Yes	Yes
Religion FE	No	No	No	Yes	Yes	Yes	Yes
District-specific Trends	No	No	No	No	Yes	Yes	Yes

Note: The dependent variable is an indicator that takes value 1 if households report having *great confidence in schools to provide good education* and 0 if they report having *hardly any confidence*; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for IHDS-2 wave (2011 − 2012) and 0 for IHDS-1 wave (2004 − 2005); controls include child's gender and grade and household size; robust standard errors in parentheses are clustered at the PSU level; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is the IHDS-1 and IHDS-2 household surveys.

Table A.7: Effect of civil unrest on private tuition (intensive margin effect)

	Pvt Tuition (Hrs/Week)			
	(1)	(2)	(3)	(4)
Kashmir x Post	-2.247*	-2.290*	0.019	-2.394
	(0.989)	(1.064)	(0.536)	(1.209)
Controls	No	Yes	No	Yes
Observations	1001	987	1001	987
R-Squared	0.305	0.332	0.085	0.129
District FE	Yes	Yes	No	No
Individual FE	No	No	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
District Trends	Yes	Yes	Yes	Yes

Note: The dependent variable is the number of hours a child avails paid private tuition per week; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu and Rajauri; *Post* is an indicator that takes value 1 for IHDS-2 wave (2011 − 2012) and 0 for IHDS-1 wave (2004 − 2005); controls include gender of the child, income, distance to school, poverty status, area of residence (rural or urban), household size, highest education of the household member, age fixed effects and religion fixed effects; robust standard errors in parentheses are clustered at PSU level; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is IHDS-1 and 2 individual panel.

Table A.8: Effect of civil unrest on learning outcomes: Alternative clustering

	Standardized Reading Score				Standardized Math Score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Kashmir x Post	-0.516***	-0.543***	-0.516***	-0.543***	-0.366**	-0.369***	-0.366***	-0.369***
	(0.114)	(0.116)	(0.111)	(0.108)	(0.141)	(0.137)	(0.098)	(0.092)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	46,596	40,736	46,596	40,736	46,242	40,466	46,242	40,466
R-Squared	0.459	0.436	0.459	0.436	0.429	0.412	0.429	0.412
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-specific Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variables, standardized reading and math scores, are standardized by year such that the mean and standard deviation in any given year is 0 and 1, respectively; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for years 2011 − 2012 and 0 for years 2007 − 2009; controls include child's gender and grade and household size; robust standard errors in parentheses are clustered at the district-year level in columns 1, 2, 5 and 6 and at the district-birth year level in columns 3, 4, 7 and 8; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table A.9: Effect of civil unrest on learning outcomes: Alternative identification

	Standardized Reading Score				Standardized Math Score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Kashmir x Post	-0.190***	-0.165***	-0.655***	-0.644***	-0.191***	-0.166***	-0.510***	-0.482***
	(0.064)	(0.056)	(0.151)	(0.153)	(0.068)	(0.060)	(0.156)	(0.155)
Controls	No	No	No	Yes	No	No	No	Yes
Observations	39,239	39,094	39,094	33,922	38,955	38,815	38,815	33,722
R-Squared	0.005	0.452	0.457	0.439	0.004	0.423	0.428	0.415
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-Year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
District-specific Trends	No	No	Yes	Yes	No	No	Yes	Yes

Note: The dependent variables, standardized reading and math scores, are standardized by year such that the mean and standard deviation in any given year is 0 and 1, respectively; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu and Rajauri; *Post* is an indicator that takes value 1 for years $2011-2012$ and 0 for years $2007-2009$; controls include child's gender and grade and household size; robust standard errors in parentheses are clustered at the village (PSU) level. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table A.10: Effect of civil unrest on learning outcomes: Linear probability estimates with alternative identification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Child can read				Child can recognize or solve			
	Letter	Word	Paragraph	Story	Digits 1-9	Digits 10-99	Subtraction	Division
Kashmir x Post	-0.107***	-0.183***	-0.325***	-0.310***	-0.165***	-0.243***	-0.314***	-0.161**
	(0.030)	(0.049)	(0.070)	(0.074)	(0.044)	(0.053)	(0.067)	(0.074)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,267	36,267	36,267	36,267	36,267	36,267	36,267	36,267
R-Squared	0.084	0.189	0.304	0.304	0.074	0.156	0.294	0.276
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: Each of the dependent variable is an indicator that takes value 1 if the child can read or solve at the level given by the model label and 0 otherwise; all models are estimated using linear probability models; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu and Rajauri; *Post* is an indicator that takes value 1 for years $2011-2012$ and 0 for years $2007-2009$; controls include child's gender and grade and household size; robust standard errors in parentheses are clustered at the village (PSU) level; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table A.11: Effect of civil unrest on learning outcomes: Total test score as dependent variable

	Total Test Score			Standardized Test Score		
	(1)	(2)	(3)	(4)	(5)	(6)
Kashmir x Post	-0.260***	-1.004***	-1.053***	-0.117***	-0.454***	-0.476***
	(0.097)	(0.258)	(0.259)	(0.044)	(0.116)	(0.117)
Controls	No	No	Yes	No	No	Yes
Mean Dep. Var.	5.42	5.42	5.59	—	—	—
Observations	46,072	46,072	40,342	46,072	46,072	40,342
R-Squared	0.489	0.495	0.474	0.486	0.492	0.472
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
District-specific Trends	No	Yes	Yes	No	Yes	Yes

Note: The dependent variable in columns 1-3 is the total test score, which is obtained by adding the reading and math test scores, while the dependent variable in columns 4-6 is the standardized total test scores such that the mean and standard deviation in any given year is 0 and 1, respectively; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for years $2011-2012$ and 0 for years $2007-2009$; controls include child's gender and grade and household size; robust standard errors in parentheses are clustered at the village (PSU) level. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table A.12: Effect of civil unrest on learning outcomes: District-cohort fixed effects

	Standardized Reading Score		Standardized Math Score	
	(1)	(2)	(3)	(4)
Kashmir x Post	-0.084*	-0.574***	-0.159***	-0.397***
	(0.047)	(0.117)	(0.049)	(0.119)
Controls	Yes	Yes	Yes	Yes
Observations	40,736	40,736	40,466	40,466
R-Squared	0.435	0.441	0.412	0.416
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Birth-Year FE	Yes	Yes	Yes	Yes
District x Birth-Year	Yes	Yes	Yes	Yes
District Specific Trend	No	Yes	No	Yes

Note: The dependent variables, standardized reading and math scores, are standardized by year such that the mean and standard deviation in any given year is 0 and 1, respectively; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for years $2011-2012$ and 0 for years $2007-2009$; controls include child's gender and grade and household size; robust standard errors in parentheses are clustered at the village (PSU) level. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table A.13: Balance test: Propensity score matching

Variable	Sample	Mean: Treated	Mean: Control	%bias	%reduct $\lvert bias \rvert$	t-test: t	t-test: $p > \lvert t \rvert$
Age	Unmatched	11.162	10.798	11.6		11.78	0.000
	Matched	11.163	11.204	-1.3	88.7	-1.56	0.118
Gender (1=Male)	Unmatched	0.527	0.544	-3.5		-3.59	0.000
	Matched	0.527	0.525	0.3	90.4	0.40	0.689
Grade	Unmatched	5.530	5.242	9.6		9.71	0.000
	Matched	5.530	5.527	0.1	99.1	0.10	0.920
HH Size	Unmatched	7.701	7.048	20.7		21.12	0.000
	Matched	7.701	7.673	0.9	95.6	1.12	0.264

Note: The treated and the control groups have been matched using nearest neighbor matching; we have employed $n = 2$ nearest neighbors with common support; logit model has been used to generate propensity scores; data source is ASER household surveys 2007-2012, excluding 2010.

Table A.14: Heterogenous effect of civil unrest of learning outcomes: linear probability model estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Child can read				Child can recognize or solve			
	Letter	Word	Paragraph	Story	Digits 1-9	Digits 10-99	Subtraction	Division
Panel A: Children with 1-5 years of schooling								
Kashmir x Post	-0.059	-0.193***	-0.249***	-0.073	-0.088**	-0.108*	-0.131*	-0.014
	(0.038)	(0.061)	(0.069)	(0.049)	(0.044)	(0.064)	(0.067)	(0.041)
Observations	22,961	22,961	22,961	22,961	22,961	22,961	22,961	22,961
R-Squared	0.073	0.174	0.198	0.117	0.064	0.158	0.207	0.092
Panel B: Children with 6-8 years of schooling								
Kashmir x Post	0.007	0.036	-0.270***	-0.498***	-0.016	0.007	-0.251***	-0.388***
	(0.037)	(0.046)	(0.077)	(0.108)	(0.042)	(0.047)	(0.074)	(0.106)
Observations	12,435	12,435	12,435	12,435	12,435	12,435	12,435	12,435
R-Squared	0.097	0.092	0.061	0.066	0.081	0.086	0.081	0.089
Panel C: Children with 9-12 years of schooling								
Kashmir x Post	0.071	0.075	-0.052	-0.390***	0.051	0.067	-0.061	-0.351***
	(0.045)	(0.047)	(0.057)	(0.082)	(0.048)	(0.050)	(0.058)	(0.088)
Observations	12,666	12,666	12,666	12,666	12,666	12,666	12,666	12,666
R-Squared	0.121	0.120	0.095	0.081	0.106	0.109	0.124	0.157
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-specific Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each of the dependent variable is an indicator that takes value 1 if the child can read or solve at the level given by the model label and 0 otherwise; all models are estimated using linear probability models; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in districts Jammu, Rajauri, Kargil and Leh(Ladakh); *Post* is an indicator that takes value 1 for years $2011 - 2012$ and 0 for years $2007 - 2009$; controls include child's gender and grade and household size; robust standard errors in parentheses are clustered at the village (PSU) level; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.

Table A.15: The effect of civil unrest on learning outcomes: All districts as controls

	Standardized Reading Score				Standardized Math Score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Kashmir x Post	-0.409***	-0.429***	-0.496***	-0.496***	-0.460***	-0.489***	-0.429***	-0.429***
	(0.093)	(0.095)	(0.099)	(0.114)	(0.101)	(0.103)	(0.102)	(0.126)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Observations	66,248	66,248	57,837	57,837	65,632	65,632	57,431	57,431
R-Squared	0.446	0.453	0.441	0.441	0.426	0.431	0.423	0.423
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-specific Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-Cohort FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Cluster by	Village(PSU)	Village(PSU)	Village(PSU)	District-Year	Village(PSU)	Village(PSU)	Village(PSU)	District-Year

Note: The dependent variables, standardized reading and math scores, are standardized by year such that the mean and standard deviation in any given year is 0 and 1, respectively; *Kashmir* is an indicator that takes value 1 for the children in districts of Kashmir and 0 for children in all districts of Jammu and Ladakh regions; *Post* is an indicator that takes value 1 for years $2011 - 2012$ and 0 for years $2007 - 2009$; controls include child's gender and grade and household size; robust standard errors in parentheses are clustered at the village (PSU) level. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; data source is ASER household surveys 2007-2012, excluding 2010.