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ABSTRACT

Crime and Human Capital in India*

It has been demonstrated that violent crime has profound effects on a number of socioeconomic outcomes. But, does day-to-day crime also shape human capital accumulation? We answer this question in the Indian context by combining multiple years of district-level data on the incidence of various types of crime with a nationally representative survey on learning achievement of school-aged children. Our empirical strategy leverages the within-district across-year variation in crime to estimate the crime-learning gradient. We show that an increase in violent crime is associated with lower achievement in reading and math, while non-violent crimes have no discernible correlation with learning outcomes. The effects are short-lived, driven by contemporaneous crime, and are similar for boys and girls. Additionally, we find that violent crimes impose greater costs on learning of children from socioeconomically disadvantaged households. We find evidence that both household-level factors (reduced child mobility and poorer mental health) and school-level factors (lower availability of teachers) are possible mechanisms underpinning these findings.

JEL Classification: I25, J24, O12
Keywords: crime, education, learning, India

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1 Introduction

High crime rates have been noted as a major risk factor in developing countries (World Bank, 2014). Studies have shown that at both the macro and micro levels, violent crimes impose significant costs for individuals, households, firms, and governments. Further, aside from the loss of life and destruction of property, people may change their behaviors to avoid crime or begin engaging in criminal activity, households may incur monetary and time costs to protect themselves from crime, firms may reduce their investment and incur productivity losses, and governments may reallocate resources from other productive avenues towards crime prevention (e.g., Soares, 2006, 2015; Pinotti, 2015; Rozo, 2018; Velasquez, 2020).

While most existing literature is based on understanding the microeconomic costs of violent episodic events – including large-scale conflicts and civil wars – on educational attainment (Verwimp et al., 2019), relatively little is known about how *day-to-day* violent crimes affect human capital accumulation in developing countries. To that end, in this paper, we examine and quantify the relationship between day-to-day crime and learning achievement of children in India. This question is particularly relevant as test scores are key predictors of labor market success (e.g., Hanushek et al., 2015; Ozawa et al., 2022). It also assumes importance in light of the 'learning crisis' that is widely documented in low-income countries, and especially in India, our study context. While enrolment rates have registered impressive increases in developing countries, it has been found that more years spent in school are not translating into higher levels of learning (Glewwe and Muralidharan, 2016; Pritchett, 2013). The World Development Report 2018 documents that a very large share of children in second grade cannot read a single word of short text or perform a two-digit subtraction, and these numbers are worryingly high in South Asia and Sub-Saharan Africa (World Bank, 2018).[1] Therefore, in such settings, where human capital levels are already low, persistent

[1]For instance, over 80 percent of children in second grade in India cannot perform these simple reading and math tasks (World Bank, 2018).

shocks in the form of day-to-day violent crimes and the environment of insecurity it creates can constitute another critical barrier to learning. Indeed, Becker and Rubinstein (2011) illustrate that the fear and stress created by small probability events leads to a divergence between the subjective and objective probabilities of risk. More specifically, individuals tend to overestimate low-probability events, and this disproportionately affects their behavior, often resulting in costly consequences.

We use multiple years of district-level data on the incidence of various types of crimes from the National Crime Records Bureau and nationally representative learning data from the Annual Status of Education Report over 2011-18 and find that an increase in violent crime hinders learning and that non-violent crimes are not associated with learning achievement. These results are robust to a variety of checks. Additionally, heterogeneity analyses reveal that violent crimes matter more adversely for learning outcomes of children with less educated mothers and those belonging to poorer households, thereby exacerbating socioeconomic inequalities in education.

Further, to add richness to our study, we leverage a wide range of available representative data sources from India to carefully examine the various mechanisms that could be driving this relationship. We investigate if the observed day-to-day crime-learning link is potentially driven by changes in the behaviors and actions of children, parents, and households (i.e., the demand-side factors) or disruption to the quantity and quality of educational inputs including teachers and schooling infrastructure (i.e., the supply-side factors). On the demand-side, we find evidence of reduced child mobility as reflected in lower school attendance and reduced participation in work for children in response to violent crime. This could be due to increased parental risk aversion as has been demonstrated in the aftermath of violent events (e.g., Brown et al., 2019; Jakiela et al., 2019). We also find evidence that violent crime leads to poorer mental health, which has also been observed in other studies (e.g., Alloush and

Bloem, 2022; Cornaglia et al., 2014; Dustmann and Fasani, 2016). Finally, on the supply side, we find that violent crime results in lower availability of teachers, with the effects being stronger for female teachers.

Our study relates to the literature on the effects of crime on educational attainment. Our work brings forth novel evidence from the South Asian context - most of the literature to date comes from the United States or Latin America. For instance, Koppensteiner and Menezes (2021) combine geo-referenced data on the precise location and timing of homicides with educational data from Sao Paulo, Brazil to find that exposure to homicides in public areas has a detrimental effect on students' test scores. Sharkey (2010) and Sharkey et al. (2014) exploit the exogenous variation in the timing of violent crime incidents relative to the timing of the standardized assessments in Chicago and New York City respectively. Both studies find that students who live in neighborhoods where violent crimes occur a week before a standardized test perform significantly worse on assessments than students who live in neighborhoods where violent crimes occur a week after the exam. Using data from Mexico, Michaelsen and Salardi (2020) and Chang and Padilla-Romo (2023) find that violent crime in proximity of schools in the week prior to standardized tests results in negative effects on test performance with no effects of violence in the week after. Further, there are a few recent papers demonstrating the deleterious impact of gun violence in academic settings on human capital accumulation in the short-, medium- and long-run (e.g., Bharadwaj et al., 2021; Cabral et al., 2022; Deb and Gangaram, 2024).

This paper is organized as follows: Section 2 describes the data sources used and Section 3 lays out the empirical framework. Section 4 describes the results, robustness checks and heterogeneity analyses. Section 5 conducts a deep dive into the various mechanisms that could explain the main results. Section 6 concludes.

2 Data

In this section, we describe the various data sources the study relies on. The main sources are described in Sections 2.1 and 2.2 below. Datasets described in Sections 2.3 - 2.5 will be used in Section 5 when we investigate the possible mechanisms.

2.1 Annual Status of Education Report

The learning outcomes come from the Annual Status of Education Report (ASER). ASER is an annual survey designed by Pratham/ASER Centre, a non-profit organization in India and implemented with the help of local partners. It attempts to cover all rural districts in the country and is carried out usually during October-November each year. ASER uses a two-stage sampling strategy, covering 320,000-350,000 households each year on average. This results in representative repeated cross-sections at the district level. We use six rounds of data between 2011 and 2018 (no surveys were conducted in 2015 and 2017).

The focus of this survey is on the educational status and learning outcomes of children. The survey is conducted at the household-level rather than in schools, which ensures that learning outcomes of enrolled and non-enrolled children can be measured. Schooling status is collected for children in the age group 3-16, and children in the age group 5-16 are tested on their ability to read simple text and do basic arithmetic.

The four questions in math consist of single-digit number recognition, double-digit number recognition, subtraction with carry over, and division. The four questions in reading (in native language) consist of reading letters, words, a short paragraph, and a short story. Therefore, the scores lie in the range of 0-4. We standardize the math and reading scores by survey year and child age.[2]

[2]While these questions might appear elementary, given the very low levels of learning documented in India and other developing countries (World Bank, 2018), such a test focusing on foundational skills is appropriate to the Indian context and shows sufficient variation in the data.

In addition to children's schooling and learning status, ASER also collects some basic information about the household (number of household members, ownership of various assets, and parents' education).

2.2 Crime in India

The crime data are taken from *Crime in India* that is published annually by the National Crime Records Bureau (NCRB), an agency of the Ministry of Home Affairs of the Government of India. These data are based on complaints filed with the police. We use data reported under the Indian Penal Code (IPC) which includes violent crimes that affect the broader population in general such as murder, culpable homicide not amounting to murder, attempt to murder, dowry deaths, hurt, kidnapping and abduction, rape, riots, robbery, dacoity, preparation and assembly for dacoity, and arson as well as non-violent crimes including theft, burglary, criminal breach of trust, cheating and counterfeiting and other miscellaneous IPC crimes.

The issue of under-reporting of crime is a standard drawback of most official police-reported data on crime.[3] As we will discuss in Section 3, the district fixed effects in our estimation framework are able to control for the district-specific time-invariant component of under-reporting.

2.3 India Human Development Survey

The India Human Development Survey (IHDS) is a nationally representative panel survey conducted by the University of Maryland in collaboration with the National Council of Applied Economic Research, New Delhi. The first round, IHDS-I, was conducted between

[3]The India Human Development Survey (IHDS) of 2005 asks households whether they have been victims of theft, burglary, physical hurt or threats. In a comparative analysis of the IHDS and NCRB data, Prasad (2013) finds that while the NCRB data is under-reported, there is a positive and significant relationship between police-recorded and victim-reported crimes.

November 2004 and October 2005 covering 41,554 households across 1,504 villages and 971 urban areas from 33 states and union territories of India (Desai et al., 2005). The second wave of the survey (IHDS-II) took place between November 2011 and October 2012, covering 42,152 households across 1,420 villages and 1,042 urban areas, and could track 83 percent of households from IHDS-I (Desai et al., 2012). In both rounds, the respondents included a person who was knowledgeable about the household's economic situation (usually the male head of the household) and an ever-married woman aged 15 to 49 years. The survey collects data on a wide range of topics including economic activity, income and consumption expenditure, asset ownership, social capital, education, health, marriage and fertility, etc.

At the household level, we have information on asset ownership and real household income (in 2004-05 Indian Rupees or INR), proxies of economic status. In keeping with the age group in ASER, we limit the sample to those aged 5-16 in the IHDS. For each child, we have information on education expenditures and engagement in work (household farm-related activities, household non-farm businesses, animal care, and external wage work).

2.4 Survey of Global Ageing and Adult Health

The Survey of Global AGEing and Adult Health (SAGE) data is collected by the World Health Organization (WHO). Wave 0 (also known as the World Health Survey) was conducted in 2003 and Wave 1 in 2007. The survey is representative of the adult population in 6 Indian states: Assam, Karnataka, Maharashtra, Rajasthan, Uttar Pradesh and West Bengal. 9,994 interviews were conducted in Wave 0 while a total of 11,230 interviews in Wave 1. As many of the same households were surveyed in both rounds, this allows us to create a panel of individuals from 7,665 households that were surveyed in both rounds.

In addition to the standard demographic characteristics (age, gender, marital status, education levels), in both rounds, there are 2 questions to assess depression and worry/anxiety that ask respondents "Overall in the last 30 days, how much of a problem did you have with feeling sad, low or depressed?" and "Overall in the last 30 days, how much of a problem did you have with worry or anxiety?" with responses on a 1-5 scale (none, mild, moderate, severe, or extreme). We construct indicator variables for 'depression' and 'anxiety', each of which takes a value of one if the respondent states 4 or 5 on the 1-5 scale, and zero otherwise. Finally, this survey also asks if the respondent's household has been the victim of a violent crime such as assault or mugging in the last 12 months.

2.5 District Information System of Education

District Information System of Education (DISE) are the official statistics of the Ministry of Human Resource Development, collected from across all districts in India. School principals report data each year on school management, student enrolment, availability of infrastructure, and number of teachers etc. From this, we construct an annual panel of approximately 1.5 million schools over 2011 to 2018.

3 Empirical specification

We estimate the relationship between district-level crime and learning attainment using the following linear regression specification:

$$Y_{idst} = \alpha_0 + \alpha_1 CrimeRate_{dst} + \sum_{l=2}^{K} \alpha_l X_{idst} + \upsilon_d + \gamma_{st} + \epsilon_{idst} \tag{1}$$

where the outcome variable, Y_{idst}, is the learning outcome from ASER (math or reading score standardized by survey year and child age) for child i in district d in state s and year t. $CrimeRate_{dst}$ is the crime rate per 1000 persons in district d of state s in year t and α_1 is our coefficient of interest. X_{isj} includes individual-level plausibly exogenous controls such as child age, child gender (takes a value 1 for female), mother's age, mother's years of education and household size. To rule out potential bias due to district-specific unobserved heterogeneity, for instance district-specific factors correlated with both learning outcomes and reported crimes, we also include district fixed effects (υ_d). This also controls for the district-specific time-invariant component of under-reporting of crime. Another source of bias could be from state- and year-specific macroeconomic factors (such as education policy changes that are a state subject) that influence educational attainment and are likely correlated with the regressors. To rule these out, we also include state-year fixed effects (γ_{st}) in all regressions. Standard errors (ϵ_{idst}) are clustered at the district level to account for any within-district serial correlation in crime over time.

Although our estimation approach aims to account for many sources of unobservable heterogeneity, there may be unobserved time-varying district-level characteristics influencing both crime rates and learning outcomes that could bias our estimates. We discuss this further in Section 4.2.

4 Results

4.1 Descriptive statistics

Table 1 presents the descriptive statistics for the ASER survey and the crime data. Panel A shows that the average score on the math and reading tests is 2.28 and 2.55 out of maximum possible scores of 4.

Panel B summarizes the number of crimes and crime rates. On average, there are 3928 total IPC crimes per year over the study period of 2011-18. Of these, on average, 797 are violent crimes and the remaining 3132 crimes are non-violent in nature. As seen in Figure 1, there is an increase in the number of IPC crimes over the study period rising gradually from 3,489 crimes in 2011 to 4,273 crimes in 2018. This is driven by the non-violent crimes steadily increasing from 2,617 in 2011 to 3,706 in 2018. The number of violent crimes increase between 2011 and 2013 from 871 to 992 and then decline thereafter to 567 crimes in 2018. Hence, the share of violent crimes over 2011-18 is approximately 24 percent but varies in the range of 15-27 percent. In terms of crime rates, calculated per 1000 district population (as per 2011 Census), the IPC crime rate is 2 per 1000, the violent crime rate is 0.41 per 1000 and the non-violent crime rate is 1.59 per 1000.

Panel C describes the covariates used from the ASER survey. 48 percent of the children are female and the average age is 10 years. 3 percent of the children are not enrolled and this is consistent with enrolment rates being very high in India. In terms of the characteristics of the mothers of the surveyed children, the average age of the mothers is 34 years and they have 4 years of education. 45 percent of children have mothers with at least primary education completed. In terms of household characteristics, the average household size is over 6 and 45 percent of children come from households with above median number of assets (calculated based on type of housing, indicator variables for availability of electricity, and ownership of mobile phone and television).[4]

4.2 Main results and robustness checks

Table 2 presents the main findings using equation (1) described in Section 3.[5] In columns 1 and 2, we regress the math and reading scores respectively on the IPC crime rate to find that total crimes have no economically or statistically significant association with learning outcomes. In columns 3 and 4, we find that an increase in the violent crime rate is associated with a decline in both math and reading scores. In terms of magnitudes, a 1 SD increase

[4]These assets were selected as they were consistently asked about in each of the six rounds of ASER.

[5]These results are robust to using the raw scores instead of standardized scores. See Table A1 in the Online Appendix.

in violent crime rate leads to a decline of 0.02 SD in the math scores and 0.014 SD in the reading scores. The magnitudes we document on the violent crimes are not negligible, especially as we are considering the effects of day-to-day violent crimes. To put these into perspective, these effect sizes are at the 40th percentile of the distributions of standardized effect sizes on learning outcomes as noted in Evans and Yuan (2022).[6] Finally, in columns 5 and 6, upon regressing test scores on non-violent crimes, it is evident that non-violent crimes have no meaningful correlation with learning outcomes. This set of results shows that it is the violent aspect of crime that leads to learning losses. This claim is further strengthened by estimating regressions where we control for both violent and non-violent crime rates simultaneously. Results in Table A2 in the Online Appendix show that only violent crime rates influence learning outcomes with coefficients on non-violent crimes being negligible. Further, these results are not driven by changes in children's enrolment or their school progression (Columns 1 and 2 in Table A3 in the Online Appendix).[7] We find these negative effects in both the sample of children who are currently enrolled and those who are not enrolled (Columns 3-6 in Table A3 in the Online Appendix).

Table 2 focuses on the contemporaneous relationship between crime rates and test scores. We next examine the issue of timing of crimes with respect to the elicitation of the learning outcomes by including lagged and lead values of crime. In columns 1 and 4 of Table 3, we control for violent crime rate in year $(t-1)$ in addition to crime in year t. While the coefficient on $CrimeRate_{dst}$ continues to be statistically significant and of a similar size as that noted in Table 2, the coefficients on crime rates in $(t-1)$ are negligible and not statistically significant, suggesting that it is only crime in the same year that matters for learning outcomes. That the lagged crime rate has no meaningful effect also highlights that

[6]Evans and Yuan (2022) create distributions of standardized effect sizes on learning outcomes based on experimental and quasi-experimental studies in low- and middle-income countries.

[7]This is not surprising as school enrolment in India is very high. Further, with the automatic grade progression in primary school due to the Right to Education Act of 2008, the proportion of children progressing on track is also high.

the effects of crime are quite short-lived. In columns 2 and 5, we control for violent crime rate in year $(t+1)$ in addition to crime in year t and this serves as a useful placebo test. Our results are reassuring in that the coefficients on the one-year leads are not statistically significant. Finally, in columns 3 and 6, we control for one year lag and lead of crime in addition to crime in year t, and we find that it is only contemporaneous crime that is significantly correlated with learning outcomes. It is also worth noting that the coefficient on $CrimeRate_{dst}$ is quite stable across the columns and robust to controlling for lags and leads of crime rates.

A second robustness check examines the concern that high crime rates may be leading to migration of higher-ability (i.e., higher-scoring) children and their families resulting in a biased estimate of our coefficient of interest. Based on the latest all-India estimates available from the 2011 Census, 62 percent of migration is within the same district and 26 percent is between districts in the same state with only 12 percent being inter-state, and this pattern is similar to that observed in the 2001 Census. Therefore, we do not envisage this as being a serious threat to our results as most of the migration is intra-district. Nevertheless, following Dustmann and Fasani (2014), we can internalize this concern by aggregating the data to a larger unit and conducting the regressions at the district level. Results in Table A4 in the Online Appendix show that our results are qualitatively similar to those estimated at the child-level, suggesting that such migration is not a concern for interpretation of our results.

Third, as the ASER scores range from 0-4, we treat them as ordinal variables. Following Chakraborty and Jayaraman (2019), we estimate linear probability models wherein the outcome is a dummy variable that takes a value of one if the child has achieved at least a certain level of mastery - separately for levels 1, 2, 3 and 4 - and zero otherwise. Results are reported for math and reading scores in Tables A5 and A6 respectively in the Online

Appendix. These results show that crime hinders learning. Table A5 show that exposure to higher crime leads to learning losses in that they are less likely to recognize double-digit numbers (column 2), carry out subtractions (column 3) and divisions (column 4) with no significant effect on basic knowledge as assessed by single-digit number recognition (column 1). For reading ability, in Table A6, we find that exposure to higher crime harms learning at all levels, but the coefficient is not statistically significant for being able to read at least a paragraph (column 3).

Fourth, we run the analysis dropping one year at a time to rule out that our results are not being driven by any one year. Results reported in Figure A1 in the Online Appendix show that the results for math scores are robust to this. However, for reading scores, we do find that while the coefficients are always negative, they fail to be statistically significant at conventional levels when excluding data for 2013 and 2018 ($p-value = 0.102$ and $p-value = 0.241$ respectively). Based on the overlapping confidence intervals, it is evident that the coefficients on the various excluding-one-year-at-a-time samples are not significantly different from one another.

Fifth, we estimate the regressions dropping one state at a time as a concern might be that some large states are driving our results. Results are presented in Figure A2 in the Online Appendix. As in the previous check, we find that results for the math scores are remarkably robust to the exclusion of states. For the reading score results, in the regression excluding the state of Madhya Pradesh, the coefficient while negative ceases to be statistically significant ($p-value = 0.161$).

Overall, these robustness checks indicate that our main results are largely robust to a number of specification checks and sample exclusions.

4.3 Heterogeneity

In this section, we examine whether the relationship between crime and learning varies based on individual, household and community characteristics.

We first examine whether effects vary based on the gender of the child and the age group in Figure 2. We split the sample into ages 5-10 and 11-16 corresponding to primary and higher levels of education. Further, boys and girls may be differently targeted by crimes and parents may assess the safety of their sons and daughters differently (e.g., Borker, 2020; Muralidharan and Prakash, 2017). These results show that the effects are statistically significant for most age-gender sub-groups. The results appear to be more adverse for the older age group and for girls, although none of these coefficients are significantly different from one another.

We next investigate whether the effects we document are heterogeneous based on the family's socioeconomic status (SES) in Table 4. We use two standard indicators of SES that are available in ASER[8]: (i) parental education measured by the mother having completed at least primary level of education; and (ii) whether the household has above median number of assets. Higher SES households may be in a better position to mitigate learning losses arising from higher crime exposure. Better educated parents have more resources and are able to provide a more conducive environment for their children and support for learning at home (e.g., Andrabi et al., 2012; Macmillan and Tominey, 2023). Indeed, studies have shown that the effects of shocks are more muted in cases where mothers are educated. For instance, Andrabi et al. (2023) find that the negative effects of the 2005 Pakistan earthquake on human capital accumulation are almost fully mitigated for children of mothers who have completed primary education. Using data from India, Nordman et al. (2022) find that education spending and child work are less susceptible to rainfall shocks in households where mothers are educated. They also show that the effects of rainfall shocks on educational

[8]Caste and religion of households - widely used proxies of socioeconomic status in India - are not elicited in ASER.

spending are smaller for socioeconomically advantaged caste groups and those from land-rich households.

In Panel A of Table 4, we split the sample based on mother's education. We construct a dummy variable that takes a value of one if the mother has completed at least primary education, and zero otherwise. We find that both math and reading scores are more adversely affected where the mother has no primary education (columns 2 and 4) as compared to where the mother has at least primary education (columns 1 and 3), and the difference is statistically significant for the reading scores ($p - value = 0.008$) but not for math scores ($p - value = 0.177$). In Panel B of Table 4, we split the sample based on whether the household that the child belongs to has above median number of assets or at or below median assets. The results here echo those observed in Panel A above. Crime exposure is associated with larger learning losses in poorer households (columns 2 and 4) and the rich-poor gap is statistically significant for the reading scores ($p-value = 0.013$) but fails to be significant at conventional levels for math scores ($p - value = 0.127$).

Third, we examine heterogeneity in impacts based on baseline crime rates in the district. *A priori* it is unclear whether exposure to crime has a more pronounced effect in areas that are generally high crime versus those that are low crime areas. Using data from Brazil, Koppensteiner and Manacorda (2016) and Koppensteiner and Menezes (2021) find that the effects of homicide exposure on birth outcomes and on learning outcomes are larger in low-crime areas. This is possibly due to individuals and households in areas where crime is endemic already having internalized the probability of crime exposure. To examine this, in Table 5, we split the sample based on whether the district had above or below median crime rates in 2010, the year just preceding the start of the study period. Consistent with the two papers described above, we find that the effects of violent crimes are considerably stronger in districts that have below median crime rates (columns 2 and 4). Moreover, the effects on reading scores vary significantly based on baseline crime exposure ($p-value = 0.098$).

Finally, we investigate whether violent crime has any distributional consequences and affects learning outcomes differently for those at who are at different parts of the test score distribution. Figures A3 and A4 in the Online Appendix report conditional quantile regressions for the standardized math and reading scores respectively. For math scores, the effect of violent crimes is negative and quite similar throughout the distribution. For reading scores, the effects of violent crimes are more adverse for those who perform poorly on the reading test (i.e., those in the 10th and 20th percentiles) while the effects are significantly smaller (albeit still negative) for those in the 80th and 90th percentiles of the reading score distribution. Together, results here and in Table 4 indicate that exposure to crime exacerbates pre-existing socioeconomic gaps in learning outcomes.

5 Mechanisms

In this section, we conduct a deep dive on the various demand-side and supply-side explanations that could be underpinning the findings reported in the previous section. Demand-side mechanisms refer to behavioral responses on the part of children, parents and households while the supply-side mechanisms refer to those on the quality and availability of schooling inputs such as teachers. As the ASER household survey does not contain information to examine these mechanisms, we leverage other large-scale representative surveys to try to comprehensively do so.

5.1 Child mobility

Crime can affect children's mobility as represented by their school attendance and participation in work. This could be due to an increase in parental risk aversion that limits children's mobility. Indeed, it has been shown that crime can lead to changes in risk attitudes with those affected by crime exposure displaying more risk aversion. For example, Jakiela and Ozier (2019) find that the unexpected post-election violence in Kenya sharply increased individual risk aversion. Using individual-level panel data collected in Mexico before and during the Mexican war on drugs, Brown et al. (2019) find that as local violent crime increases, there is a rise in risk aversion.

As previously discussed, while there is no correlation between violent crime and school enrolment and progression rates, children could still be attending school less. While nationally representative individual-level data on school attendance for India is not available, the ASER School Survey collects enrolment and attendance data at the grade level.[9] Regressing attendance rates (i.e., number of children attending on the day of the survey team visit as a proportion of number of children enrolled) on violent crime shows that violent crime is negatively associated with student attendance in primary school ($beta$ = -0.018; SE = 0.004; $p-value$ < 0.001) but not in upper primary schools ($beta$ = -0.01; SE = 0.006; $p-value$ = 0.13).

We use further proxies of child mobility from the two waves of India Human Development Survey (IHDS) as described in Section 2.3. Engagement in work or economic activity is a widely used measure of mobility, particularly in research on violence against women (e.g., Borker, 2020; Siddique, 2022). The IHDS contains information on children's work in farm work, non-farm household enterprises, animal care and wage work. We also construct a binary measure for 'any work' that takes a value of one if the child is involved in any of these types of work, and zero otherwise. Estimating regressions using household fixed effects

[9] In addition to the household surveys conducted by ASER (as described in Section 2.1), every survey year, the survey team also visits a government primary school (grades 1-5) or upper primary school (grades 1-8) in each sampled village. The respondent for these surveys is either the school principal or a senior teacher. The school information is recorded based either on the enumerators' observations (such as student attendance or teacher presence or availability of facilities) or information provided by the school (such as student enrolment based on class register, number of teachers employed etc.). We use this data for six rounds spanning 2011 to 2018.

and survey month-year fixed effects, in Table 6, we see that violent crime negatively affects children's propensity to do any work (column 1) as well as all other types of work, excluding wage work.

These results suggest that reduced child mobility on account of violent crime could play a role in explaining our results on children's learning.

5.2 Household economic status

Exposure to crime can affect households' economic status which can in turn affect allocation of resources towards education. For example, Velasquez (2020) finds that drug-related violent crime in Mexico adversely affected employment status and hours worked, especially for self-employed workers who were the most vulnerable to the economic effects of local violence.

We use data from IHDS household-level panel, and use log of real household income (in 2004-05 Indian Rupees or INR) and a PCA index of various household assets as the two proxies of household economic status. In Table 7, we see that exposure to crime has no statistically significant effects on either income or assets, indicating that this channel does not play an important role in explaining our results on test scores.

5.3 Mental health

There is now a small but rapidly growing literature showing that crime imposes psychological costs not just through direct victimization but also through local exposure. For instance, Dustmann and Fasani (2016) find that exposure to crime worsens mental health and psychological well-being in the United Kingdom. Cornaglia et al. (2014) corroborate this finding for Australia. More recently, Alloush and Bloem (2022) document a similar result for South Africa. The intuition is that exposure to neighborhood violence increases the fear of being directly victimized, results in a feeling of reduced freedoms due to limitations on mobility and behaviour and a need to invest in strategies to avoid victimization, all of which impose psychological costs (Dustmann and Fasani, 2016). Further, studies have shown that exposure to crime can impair children's attention and impulse control which has implications for their academic performance (e.g., Sharkey et al., 2012; Michaelsen and Salardi, 2020; Chang and Padilla-Romo, 2023). Parental stress and insecurity caused by community violence can also be transmitted to children.

To that end, we examine whether exposure to crime worsens mental health in India. We do so using the two waves of the Survey of Global Ageing and Adult Health (SAGE) described in Section 2.4. As individuals from over 7,600 households were interviewed in both 2003 and 2007, we can use household- and survey-year fixed effects in our estimation framework. The outcomes are measures of depression and worry/anxiety. In columns 1 and 2 of Table 8, the outcomes are binary measures of depression and worry/anxiety while in columns 3 and 4, they are continuous measures on a 1-5 scale. The results show that being a victim of crime increases the likelihood of depression and anxiety as well as the levels of these variables. This finding is consistent with those from other studies described above, and provides a plausible explanation for why exposure to violent crime affects educational outcomes.

5.4 School inputs

In this section, we discuss possible school-related supply-side responses to crime that can affect children's learning outcomes. Exposure to crime can affect teacher absenteeism by making the environment unsafe for teachers to travel to school. It can also increase teacher and principal turnover (e.g., Monteiro and Rocha, 2017).[10]

[10]Using the ASER School Survey, we do not find violent crime to be correlated with any of the infrastructure-related variables such as availability of playgrounds, library books, computers, mid-day meals, and toilets for boys and girls (see Table A7 in the Online Appendix. This is a reassuring result as we do not expect year-on-year variations in day-to-day crime to affect availability of infrastructure.

To examine the effects of crime on teacher availability, we use data from the DISE as described in Section 2.5. The DISE contains information on the total number of (female and male) teachers employed by the school. Further, for each school, for grades 1-4 and grades 5-8, the working hours per day of teachers are also reported. We use these measures as outcomes in Table 9. As we have a school-level panel, the regression analysis relies on school fixed effects and year fixed effects with standard errors clustered at the pincode (or postcode) level. Column 1 show that exposure to violent crime is associated with a lower stock of teachers and the effects on the number of female teachers are larger than those on the male teachers (columns 2 and 3). Further, columns 4 and 5 show that an increase in violent crime rate is associated with higher number of working hours per day for teachers in primary and upper primary grades. This suggests that with fewer teachers on hand, the working hours are higher for those that remain in employment. As student enrolment is unchanged, this also implies higher student-teacher ratios which are associated with poorer learning.[11]

To summarize, we find support for the following mechanisms that could explain the negative association between violent crime and children's learning outcomes: reduced mobility of children, worse mental health, and lower availability of teachers in schools. However, a caveat associated with using different datasets to examine mechanisms implies that we are unable to comment on the relative importance of each of these channels.

6 Conclusion

This paper estimates the effect of neighbourhood crime on human capital accumulation, focusing on learning outcomes of children in India. We combine multiple years of district-level data on incidence of crime from the National Crime Records Bureau with information

[11] A district-level regression with the number of schools as the outcome shows that these findings are not driven by the number of schools changing in response to violent crime ($\beta = 1.96$; $SE = 4.3$).

from the nationally representative Annual Survey of Education Report on math and reading scores of children between 5 and 16 years of age. We use a district fixed effects model and account for differential time-trends across states, along with plausibly exogenous individual and household controls. Our empirical strategy leverages the within-district across-years variation in crime to estimate the crime-learning gradient.

We find that an increase in violent crime impedes learning with non-violent crimes having no effect. These results are robust to a range of checks. We also demonstrate that the relationship between crime and learning is heterogeneous based on socioeconomic status of the children, with exposure to violent crime widening learning gaps between relatively more and less well-off households. We do not find significant heterogeneities based on child age and gender. Further, we attempt to rigorously examine the potential channels by leveraging a variety of representative datasets from India. We find support for the following mechanisms that can explain the negative effects of violent crime on children's learning outcomes: on the demand-side, we find evidence of poorer mental health and reduced child mobility, and on the supply-side, we find lower availability of teachers because of violent crime.

While most existing literature, with a few exceptions, has focused on episodic violence, this study sheds light on the effects of day-to-day crime on human capital accumulation, an often overlooked cost of such crime. Further, the fact that crime experienced routinely by people in their daily lives widens socioeconomic disparities in learning also has implications for equitable growth and development. While our estimates are for India, we believe these findings can extend to other low- and middle-income countries where such crime is endemic.

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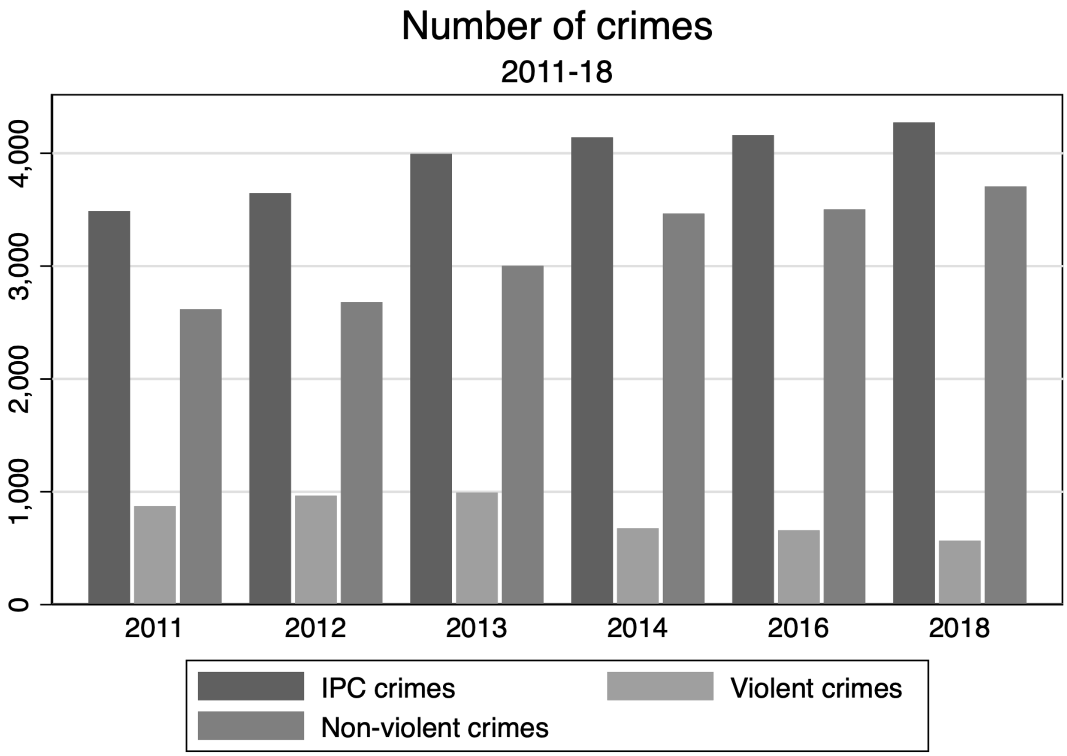
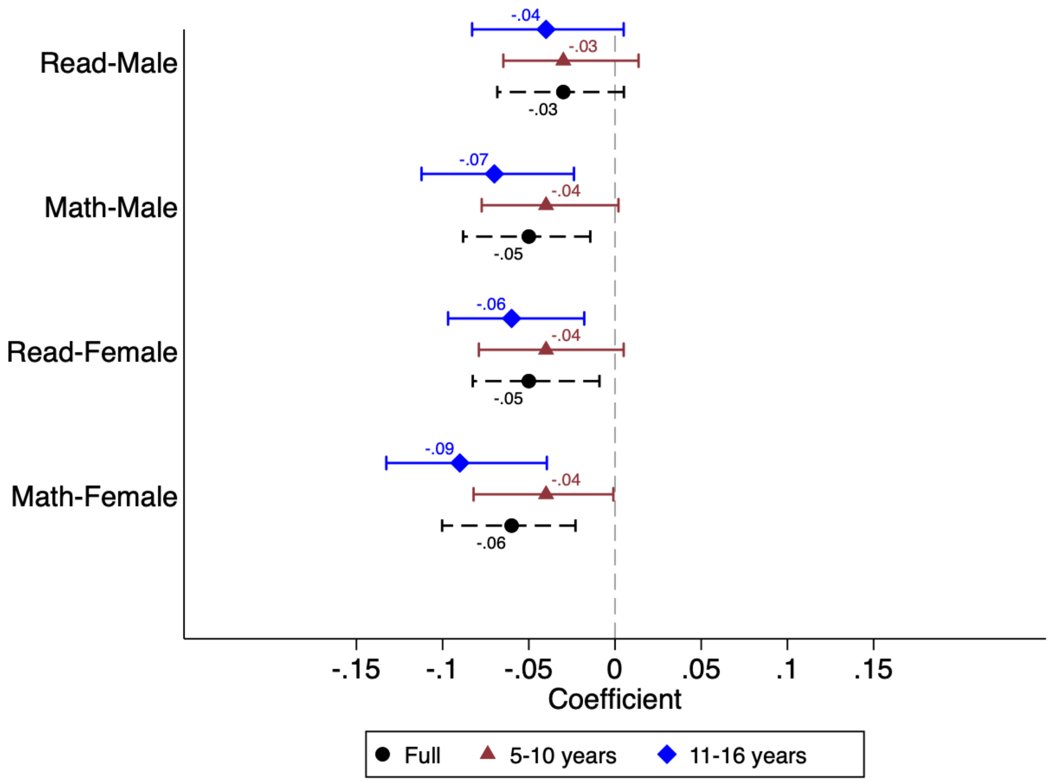
Figure 1: Crimes in India, 2011-2018



Source: Authors' calculations using data from National Crime Records Bureau (NCRB).

Figure 2: Heterogeneity by age and gender



Notes: This figure shows point estimates and 95% confidence intervals.

Table 1: Summary statistics

	Mean	SD
Panel A: Learning outcomes		
Math Score (0-4)	2.28	1.33
Reading Score (0-4)	2.55	1.50
Panel B: Crime variables		
Total IPC crime	3928.21	4255.07
Violent crimes	796.50	854.69
Non-violent crimes	3131.72	3731.36
Total IPC crime per 1000	2.00	2.31
Violent crime per 1000	0.41	0.38
Non-violent crime per 1000	1.60	2.04
Panel C: Other variables		
Female child (=1)	0.48	0.50
Age of child (in years)	10.31	3.26
Not in school (=1)	0.03	0.17
Above median assets (=1)	0.45	0.50
Mother's age (in years)	34.31	7.56
Mother at least primary educated (=1)	0.45	0.50
Mother's years of education	4.22	4.58
Household size	6.52	3.17
Observations	2495078	

Notes: Panels A and C are computed using the Annual Status of Education Report (ASER) survey. Panel B is computed using data from the National Crime Records Bureau.

Table 2: Effect of crime on standardized test scores

	Math Score	Reading Score	Math Score	Reading Score	Math Score	Reading Score
	(1)	(2)	(3)	(4)	(5)	(6)
Total IPC crime per 1000	-0.007	-0.001				
	(0.007)	(0.005)				
Violent crime per 1000			-0.057***	-0.039**		
			(0.018)	(0.018)		
Non-violent crime per 1000					0.001	0.004
					(0.007)	(0.005)
R-squared	0.162	0.120	0.162	0.120	0.162	0.120
Observations	2,385,033	2,385,033	2,385,033	2,385,033	2,385,033	2,385,033
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The math and reading scores standardized by survey year and age are from the ASER survey. The crime data are from the NCRB. Controls include child's age, child's gender, mother's age, mother's years of education and household size. Standard errors clustered at the district level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 3: Including lags and leads of crimes

	Math Score			Reading score		
	(1)	(2)	(3)	(4)	(5)	(6)
Violent crime per 1000	-0.058***	-0.057***	-0.058***	-0.038**	-0.042**	-0.041**
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Violent crime per 1000 (t-1)	0.002		0.001	-0.005		-0.004
	(0.006)		(0.007)	(0.009)		(0.009)
Violent crime per 1000 (t+1)		-0.002	-0.001		0.008	0.008
		(0.008)	(0.008)		(0.007)	(0.007)
R-squared	0.162	0.162	0.162	0.120	0.120	0.120
Observations	2,371,826	2,371,826	2,371,826	2,371,826	2,371,826	2,371,826
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The math and reading scores standardized by survey year and age are from the ASER survey. The crime data are from the NCRB. Controls include child's age, child's gender, mother's age, mother's years of education and household size. Standard errors clustered at the district level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 4: Heterogeneity by socioeconomic status

	Panel A: Heterogeneity by maternal education			
	Math Score		Reading Score	
	At least primary educated	No primary education	At least primary educated	No primary education
	(1)	(2)	(3)	(4)
Violent crime per 1000	-0.038**	-0.078***	0.001	-0.074***
	(0.018)	(0.024)	(0.015)	(0.024)
P-value of diff		.177		.008
R-squared	0.095	0.095	0.062	0.068
Observations	1,117,467	1,290,030	1,117,467	1,290,030
Controls	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes

	Panel B: Heterogeneity by wealth			
	Math Score		Reading Score	
	$>$ median assets	$\leq$ median assets	$>$ median assets	$\leq$ median assets
	(1)	(2)	(3)	(4)
Violent crime per 1000	-0.030	-0.074***	0.004	-0.066***
	(0.018)	(0.023)	(0.016)	(0.023)
P-value of diff		.127		.013
R-squared	0.131	0.138	0.093	0.104
Observations	1,046,263	1,244,379	1,046,263	1,244,379
Controls	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes

Notes: The math and reading scores standardized by survey year and age are from the ASER survey. The crime data are from the NCRB. Controls include child's age, child's gender, mother's age, and household size. Standard errors clustered at the district level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 5: Heterogeneity by baseline crime rates

	Math Score		Reading Score	
	> median crime rate (1)	≤ median crime rate (2)	> median crime rate (3)	≤ median crime rate (4)
Violent crime per 1000	-0.043*	-0.109**	-0.015	-0.096**
	(0.022)	(0.047)	(0.022)	(0.043)
P-value of diff		.21		.098
R-squared	0.159	0.163	0.114	0.126
Observations	1,120,799	1,132,487	1,120,799	1,132,487
Controls	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes

Notes: The math and reading scores standardized by survey year and age are from the ASER survey. The crime data are from the NCRB. Baseline crime rates are from 2010. Controls include child's age, child's gender, mother's age, mother's years of education and household size. Standard errors clustered at the district level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 6: Effect of violent crime on child work

	Any work	Farm work	Non-farm work	Animal care	Wage work
	(1)	(2)	(3)	(4)	(5)
Violent crime per 1000	-0.076***	-0.056**	-0.005**	-0.057***	-0.005
	(0.025)	(0.022)	(0.002)	(0.022)	(0.005)
Mean of dep. var.	0.149	0.080	0.010	0.090	0.027
R-squared	0.181	0.108	0.015	0.097	0.081
Observations	76,385	76,386	76,386	76,386	76,384
Controls	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Survey month-year FE	Yes	Yes	Yes	Yes	Yes

Notes: The outcome variables are all binary and are from the India Human Development Surveys of 2004-05 and 2011-12. The crime data are from the NCRB. Standard errors clustered at the district level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 7: Effect of violent crime on household economic status

	Log (Household Income) (1)	Asset Index (2)
Violent crime per 1000	-0.037	0.024
	(0.038)	(0.030)
Mean of dep. var.	10.324	10.557
R-squared	0.028	0.075
Observations	55,773	56,371
Controls	Yes	Yes
Household FE	Yes	Yes
Survey month-year FE	Yes	Yes

Notes: The outcome variables are from the India Human Development Surveys of 2004-05 and 2011-12. These regressions are at the household level. The crime data are from the NCRB. Standard errors clustered at the district level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 8: Victimization and mental health

	Depressed	Worried	Depression (cont.)	Worry (cont.)
	(1)	(2)	(3)	(4)
Victimization	0.069***	0.057*	0.237***	0.241***
	(0.024)	(0.031)	(0.085)	(0.087)
Mean of dep. var.	0.092	0.131	1.809	1.962
R-squared	0.485	0.494	0.530	0.537
Observations	15,246	15,246	15,246	15,246
Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: The data are from the SAGE waves 0 and 1. Victimization is a dummy variable that takes a value 1 if the household reports being the victim of assault or mugging in the last 12 months. Controls include age, gender, marital status, education dummies for primary, secondary, high school and university (below primary being omitted). Standard errors clustered at the district level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table 9: Violent crime and teacher availability

	Total teachers	Female teachers	Male teachers	Working hours/day (grades 1-4)	Working hours/day (grades 5-8)
	(1)	(2)	(3)	(4)	(5)
Violent crime per 1000	-0.071***	-0.057***	-0.014*	0.160***	0.220***
	(0.017)	(0.012)	(0.007)	(0.020)	(0.028)
Mean of dep. var.	5.285	2.450	2.834	5.988	5.967
R-squared	0.886	0.889	0.869	0.321	0.308
Observations	10,474,896	10,474,896	10,474,896	8,531,835	3,835,122
School FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: The outcomes are from DISE data. The crime data are from the NCRB. Standard errors clustered at the pincode (postcode) level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

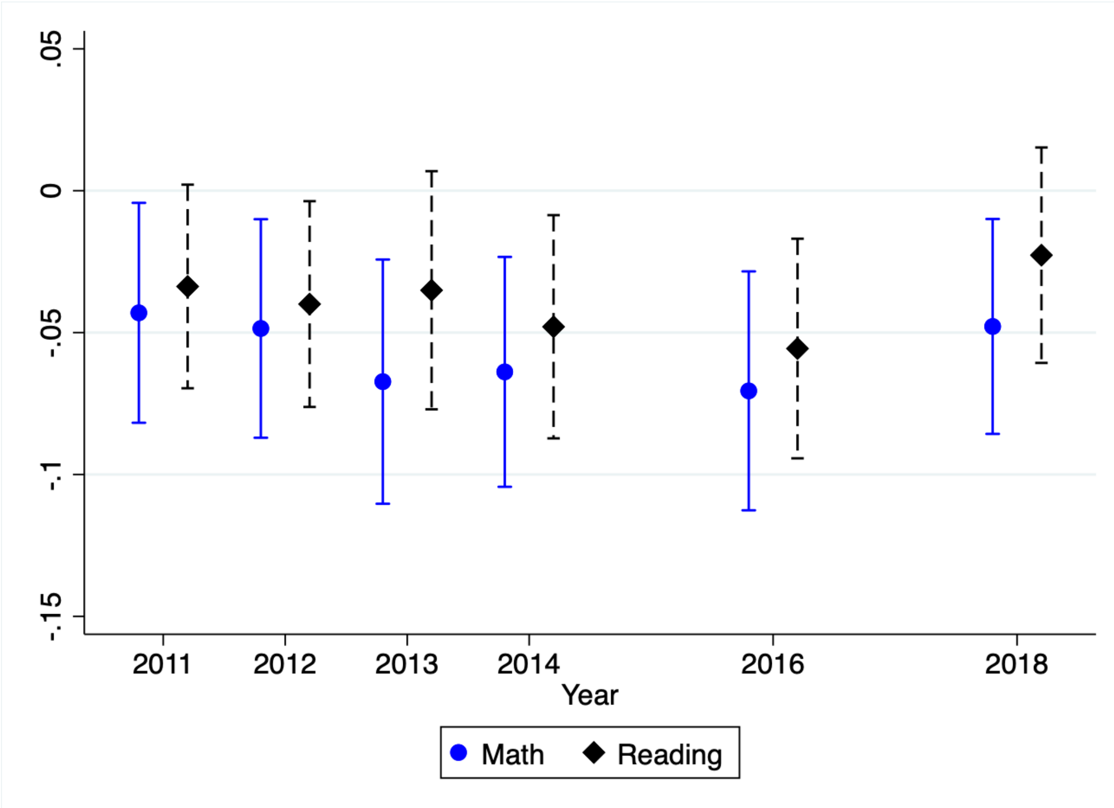
Online Appendix

Crime and Human Capital in India

Sharma and Sunder

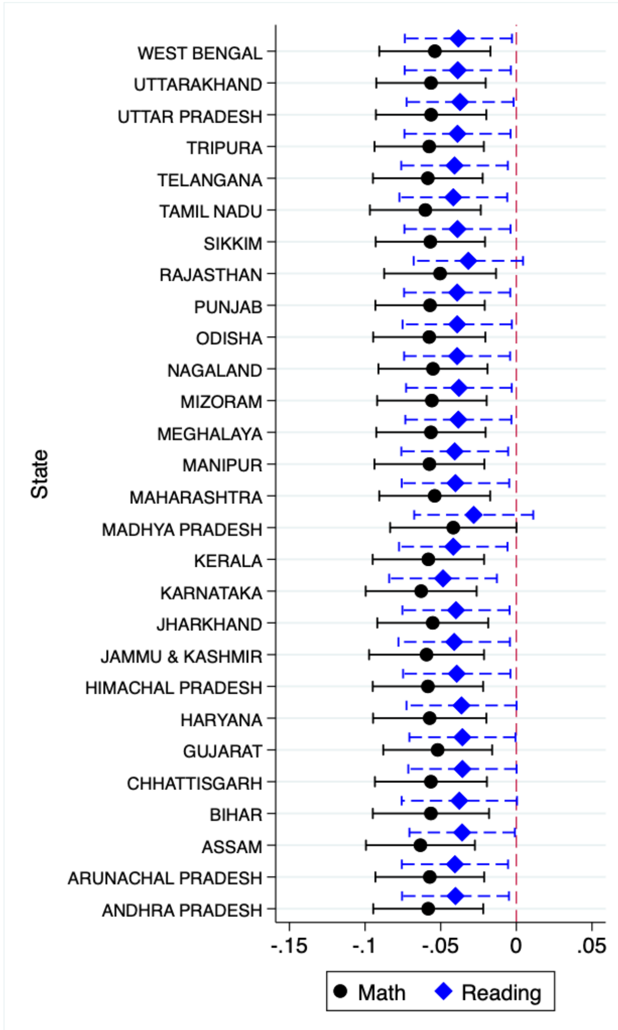
[NOT FOR PUBLICATION]

Figure A1: Dropping one year at a time



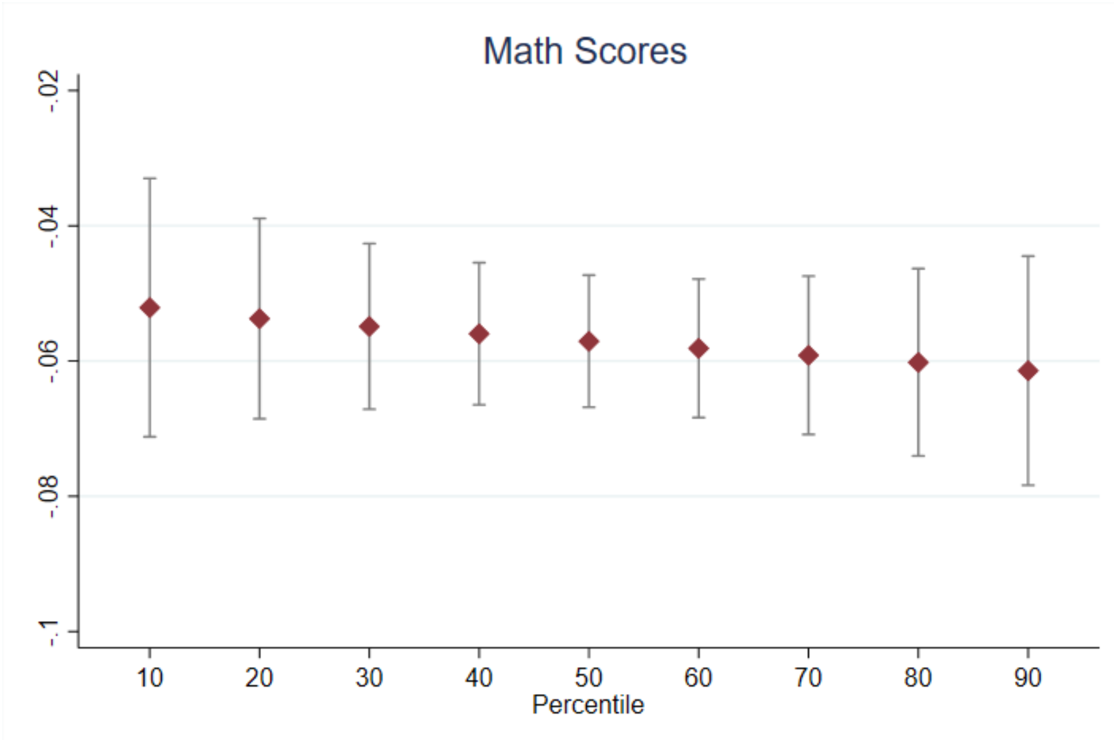
Notes: This figure shows point estimates and 95% confidence intervals.

Figure A2: Dropping one state at a time



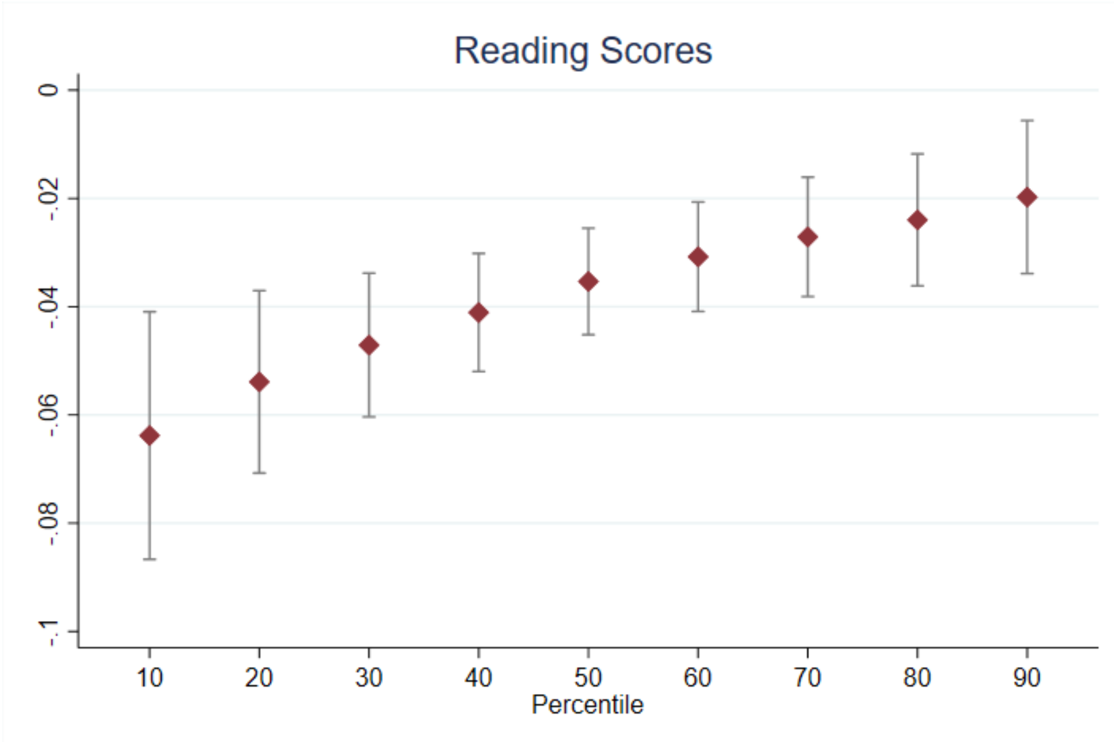
Notes: This figure shows point estimates and 95% confidence intervals.

Figure A3: Quantile regressions - Math Scores



Notes: This figure shows point estimates and 95% confidence intervals at various points of the conditional distribution of standardized math scores.

Figure A4: Quantile regressions - Reading Scores



Notes: This figure shows point estimates and 95% confidence intervals at various points of the conditional distribution of standardized reading scores.

Table A1: Effect of crime on raw test scores

	Math Score	Reading Score	Math Score	Reading Score	Math Score	Reading Score
	(1)	(2)	(3)	(4)	(5)	(6)
Total IPC crime per 1000	-0.007	-0.001				
	(0.007)	(0.006)				
Violent crime per 1000			-0.061***	-0.043**		
			(0.019)	(0.020)		
Non-violent crime per 1000					0.001	0.005
					(0.008)	(0.006)
R-squared	0.479	0.491	0.479	0.491	0.479	0.491
Observations	2,385,033	2,385,033	2,385,033	2,385,033	2,385,033	2,385,033
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The raw math and reading scores are from the ASER survey. The crime data are from the NCRB. Controls include child's age, child's gender, mother's age, mother's years of education and household size. Standard errors clustered at the district level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table A2: Controlling for non-violent crime

	Math Score (1)	Reading Score (2)
Violent crime per 1000	-0.057***	-0.038**
	(0.018)	(0.018)
Non-violent crime per 1000	-0.002	0.002
	(0.007)	(0.005)
R-squared	0.162	0.120
Observations	2,385,033	2,385,033
Controls	Yes	Yes
State-Year FE	Yes	Yes
District FE	Yes	Yes

Notes: The math and reading scores standardized by survey year and age are from the ASER survey. The crime data are from the NCRB. Controls include child's age, child's gender, mother's age, mother's years of education and household size. Standard errors clustered at the district level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table A3: Effect of violent crimes on educational outcomes (in-school & not in-school sample)

			In School		Not In School	
	Enrolled	On Track	Math Score	Reading Score	Math Score	Reading Score
	(1)	(2)	(3)	(4)	(5)	(6)
Violent crime per 1000	-0.001	0.003	-0.055***	-0.035**	-0.089*	-0.136**
	(0.002)	(0.004)	(0.018)	(0.017)	(0.049)	(0.059)
R-squared	0.065	0.136	0.155	0.114	0.168	0.162
Observations	2,385,033	2,144,682	2,318,558	2,324,175	70,303	70,506
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The outcome variables are from the ASER survey. The math and reading scores are standardized by survey year and age. The crime data are from the NCRB. Controls include child's age, child's gender, mother's age, mother's years of education and household size. Standard errors clustered at the district level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table A4: District-level analysis

	Math Score (1)	Reading Score (2)	Math Score (3)	Reading Score (4)	Math Score (5)	Reading Score (6)
Total IPC crime per 1000	-0.009	-0.005				
	(0.006)	(0.005)				
Total violent crime per 1000			-0.047**	-0.032*		
			(0.019)	(0.019)		
Total non-violent crime per 1000					-0.004	-0.001
					(0.007)	(0.005)
R-squared	0.886	0.871	0.887	0.871	0.886	0.871
Observations	3,359	3,359	3,359	3,359	3,359	3,359
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: These regressions are at the district level. The math and reading scores standardized by survey year and age are from the ASER survey. The crime data are from the NCRB. Standard errors clustered at the district level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table A5: Treating math scores as ordinal

	≥ 1	≥ 2	≥ 3	$= 4$
	(1)	(2)	(3)	(4)
Violent crime per 1000	-0.004	-0.017***	-0.023***	-0.016**
	(0.004)	(0.006)	(0.007)	(0.006)
R-squared	0.248	0.381	0.344	0.268
Observations	2,385,033	2,385,033	2,385,033	2,385,033
Controls	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes

Notes: The dependent variable is a dummy variable equal to 1 if the child has mastered at least the skill level indicated in the ASER math test. The crime data are from the NCRB. Controls include child's age, child's gender, mother's age, mother's years of education and household size. Standard errors clustered at the district level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table A6: Treating reading scores as ordinal

	≥ 1	≥ 2	≥ 3	$= 4$
	(1)	(2)	(3)	(4)
Violent crime per 1000	-0.007*	-0.013**	-0.010	-0.012*
	(0.004)	(0.006)	(0.007)	(0.007)
R-squared	0.262	0.391	0.413	0.366
Observations	2,385,033	2,385,033	2,385,033	2,385,033
Controls	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes

Notes: The dependent variable is a dummy variable equal to 1 if the child has mastered at least the skill level indicated in the ASER reading test. The crime data are from the NCRB. Controls include child's age, child's gender, mother's age, mother's years of education and household size. Standard errors clustered at the district level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.

Table A7: Violent crime and school infrastructure

	Playground	Library books	Computers	Mid-day meals	Boys' toilets	Girls' toilets
	(1)	(2)	(3)	(4)	(5)	(6)
Violent crime per 1000	-0.013	-0.004	0.006	0.004	-0.003	0.006
	(0.018)	(0.014)	(0.009)	(0.018)	(0.015)	(0.013)
Mean of dep. var.	0.638	0.749	0.201	0.866	0.903	0.915
R-squared	0.136	0.231	0.358	0.229	0.076	0.072
Observations	90,121	89,979	89,891	89,944	45,806	50,447
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The outcomes are from all binary variables from the ASER School Survey. The crime data are from the NCRB. Standard errors clustered at the district level are reported in parentheses. * significant at 10%,** significant at 5%,*** significant at 1%.