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Crime and human capital in India[☆]

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ABSTRACT

Violent crime profoundly affects several 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 crime data with a representative survey on learning achievement of school-aged children. Our empirical strategy leverages the district-year variation in crime to estimate the crime-learning gradient. We find 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. These associations hold similarly for boys and girls. Further, children from socioeconomically disadvantaged households show stronger negative associations. We document evidence that both household-level factors (reduced child mobility, lower adult engagement in work, and poorer mental health) and school-level factors (lower availability of teachers) are possible mechanisms underpinning these findings.

1. Introduction

Elevated crime rates are a significant risk factor in developing countries (World Bank, 2014). Studies show that at both the macro and micro levels, violent crimes impose significant costs for individuals, households, firms, and governments (e.g., Pinotti, 2015; Rozo, 2018; Soares, 2006; Velasquez, 2020). However, while most existing literature is based on understanding the microeconomic costs of violent episodic events such as large-scale conflicts, drug-related violence or endemic violence in high criminality areas, relatively little is known about how *day-to-day* violent crimes – that take place routinely in societies – are associated with human capital formation in developing countries. To that end, in this paper, we examine the relationship between day-to-day crime and learning achievement of children in India. This question is relevant as test scores are key predictors of labour market success (e.g., Hanushek, Schwerdt, Wiederhold, & Woessmann, 2015; Ozawa et al., 2022), and are more salient in low-income countries due to the low achievement levels of students. This is because although enrolment rates have registered impressive increases in developing countries, this has not translated into higher levels of learning (Glewwe & Muralidharan, 2016). The World Development Report 2018 documents this '*learning crisis*' – almost half the students 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, repeated shocks in the form of day-to-day violent crimes and the environment of insecurity they create can constitute another critical barrier to learning.

Our empirical strategy uses secular (natural) variations in district-level crime over time to examine the association between exposure to violent crime and learning outcomes (test scores), while controlling for district and time fixed effects. We combine multiple years of district-level data on the incidence of various types of crimes from the National Crime Records Bureau and representative child-level learning data from the Annual Status of Education Report over 2011–18. We find that increases in violent crime are associated with poorer learning outcomes, while non-violent crimes have no such association with learning. We observe that contemporaneous crime is generally associated with lower test scores, even upon inclusion of lagged and lead values of the violent crime rate. Heterogeneity analyses reveal that violent crimes correlate

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

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more strongly with adverse learning outcomes for children with less educated mothers and those belonging to poorer households, thereby exacerbating socioeconomic inequalities in education. Our findings are robust to a variety of checks including the use of alternative household-level panel data – with tests conducted for children aged 8–11 years of age – that enable the use of household fixed effects, as well as the inclusion of district-level time-varying characteristics such as district-level economic activity (proxied by night lights) and state-time trends. Our results are also robust to allowing for differential time trends across districts, by interacting district characteristics with linear time trends.

Further, to add richness to our study, we draw on 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 violent crime-learning link may be related to changes in the behaviours 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). We observe patterns consistent with both sets of factors being relevant. On the demand-side, we document reduced child mobility as reflected in lower school attendance and reduced participation in work for children in response to increases in violent crime. This could be due to increased parental risk aversion as shown in the aftermath of violent events (e.g., Brown, Montalva, Thomas, & Velásquez, 2019; Jakiela & Ozier, 2019). We also find some evidence of a worsening of adults' labour force participation in response to violent crime. Further, violent crime is correlated with worse mental health, which aligns with other studies (e.g., Alloush & Bloem, 2022; Cornaglia, Feldman, & Leigh, 2014; Dustmann & Fasani, 2016). Finally, on the supply side, we find that violent crime is associated with lower availability of teachers, especially for female teachers.

Our study makes two key contributions. First, we focus on violent crimes that take place in society generally, and do not focus on specific types of violent crimes. For example, the bulk of literature is focused on violent crime in areas characterized by high criminality or unrest (e.g., Alloush & Bloem, 2022; Koppensteiner & Manacorda, 2016), violence in areas with high prevalence of drugs and drug cartels (e.g., Monteiro & Rocha, 2017; Chang & Padilla-Romo, 2023; Moya, 2018), and wars or other large mortality events (Verwimp, Justino, and Brück (2019) provides an overview). By exploring more *general* type of violent crime, we add to the literature by providing a more comprehensive understanding of (a) the negative associations between routinely occurring violent crimes and human capital accumulation, and (b) the plausible mechanisms through which such associations may operate. In doing so, we present evidence that may be more applicable to a wider variety of contexts as compared to studies focusing on acutely violent events and regions.

Second, we add to the large and growing literature on crime and its effects on educational outcomes by bringing forth evidence from the Asian context, more specifically from South Asia.[2] Most existing literature comes from the United States or Latin America. For instance, Koppensteiner and Menezes (2021) combine georeferenced 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, Schwartz, Ellen, and Lacoe (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 neighbourhoods where violent crimes occur a week before a standardized test perform significantly worse on assessments than students who live in neighbourhoods where violent crimes occur a week after the exam. Using data from Mexico, Chang and Padilla-Romo (2023) and Michaelsen and Salardi (2020) 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, a few recent papers demonstrate the deleterious impact of gun violence in academic settings on human capital accumulation in the short-, medium- and long-run (e.g., Bharadwaj, Bhuller, Loken, & Wentzel, 2021; Cabral, Kim, Rossin-Slater, Schnell, & Schwandt, 2025; Deb & 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 explores various mechanisms that could explain the main results. Section 6 concludes.

2. Data

In this section, we describe the various data sources that the study relies on. The main sources are described in Sections 2.1 and 2.2 below. The data sets described in Sections 2.3–2.5 are used for additional analyses, including mechanisms.

2.1. Annual Status of Education Report

The learning outcomes come from the Annual Status of Education Report (ASER). Pratham/ASER Centre, a non-profit organization in India, designs the survey and implements it annually in partnership with local organizations. The survey typically covers all rural districts in the country and takes place during October and November. ASER uses a two-stage sampling strategy and surveys approximately 320,000–350,000 households annually, resulting in repeated cross-sections at the district level (the lowest identifiable level). We use six rounds of data from 2011 to 2018 (ASER did not conduct surveys in 2015 and 2017).

The survey focuses on the educational status and learning outcomes of children. Enumerators conduct the survey at the household level rather than in schools, which allows them to capture learning outcomes for both enrolled and non-enrolled children. They collect schooling status for children aged 3–16 and test children aged 5–16 on their ability to read simple text and perform basic arithmetic.

The four math questions assess single-digit number recognition, double-digit number recognition, subtraction with carry over, and division. The four reading questions (in the local language) include reading letters, words, a short paragraph, and a short story. These assessments yield scores ranging from 0 to 4. We standardize the math and reading scores by survey year and child age.[3]

In addition to children's schooling and learning status, ASER also gathers basic household data, including household size, asset ownership, and parents' education levels.

2.2. Crime in India

We obtain crime data from *Crime in India*, an annual publication by the National Crime Records Bureau (NCRB), an agency under the Ministry of Home Affairs, Government of India. We use annual district-level crime data – the most disaggregated level available – for the period 2011–2018. These data reflect complaints that individuals file with the police.[4]

[2] Additionally, we present *national-level* evidence from the most populous country in the world, as compared to various studies that focus on selected regions within countries.

[3] 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.

[4] Under-reporting remains a common limitation of official police-reported crime statistics. The India Human Development Survey (IHDS) of 2005 asks households whether they experienced theft, burglary, physical harm, or threats. In a comparative analysis, Prasad (2013) finds that although NCRB data are under-reported, they are positively and significantly correlated with victim-reported crimes.

We focus on crimes reported under the Indian Penal Code (IPC), which includes both violent and non-violent offences. Violent crimes affecting the general public include 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. Non-violent crimes include theft, burglary, criminal breach of trust, cheating, counterfeiting, and other miscellaneous IPC offences.

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. IHDS-I, the first round, took place between November 2004 and October 2005 and covered 41,554 households across 33 states and union territories of India. The second round, IHDS-II, followed between November 2011 and October 2012, surveying 42,152 households and tracking 83 percent of those from IHDS-I. In both waves, enumerators interviewed a respondent knowledgeable about the household's economic situation and an ever-married woman aged 15 to 49. The survey collects information on a wide range of topics including economic activity, income, consumption, asset ownership, social capital, education, health, and fertility.

We use IHDS data on adults' participation in work, household-level asset ownership and household-level real income (in 2004–05 Indian Rupees or INR) as proxies for economic status. To align with the ASER sample, we restrict the child sample to those aged 5–16. For each child, the survey records whether they engage in household farm work, non-farm businesses, animal care, or external wage work. IHDS also includes a testing module in which all children aged 8–11 in each household take short reading, writing, and math assessments. These scores range from zero to four.

2.4. Study of Global Ageing and Adult Health

The World Health Organization (WHO) collects the Study of Global AGEing and Adult Health (SAGE). Wave 0 was conducted in 2003 and surveyed 9994 households, and Wave 1 in 2007 with 11,230 households. The survey is representative of the adult population in six Indian states: Assam, Karnataka, Maharashtra, Rajasthan, Uttar Pradesh, and West Bengal. As many households participated in both waves, we construct a panel of individuals from 7665 households surveyed in both rounds.

In addition to standard socio-demographic characteristics, both survey rounds include two questions assessing mental health. Respondents are asked: "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?" Responses are recorded on a five-point scale (none, mild, moderate, severe, or extreme). We construct binary indicators for 'depression' and 'anxiety', coding each as one if the respondent selects "severe" or "extreme" (4 or 5 on the scale), and zero otherwise. The survey also asks if the respondent's household experienced a violent crime such as assault or mugging within the past 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 spanning the years 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 math or reading test score (standardized by survey year and child age) for child i in district d in state s in year t, as reported in ASER. $CrimeRate_{dst}$ is the crime rate per 1000 people in district d in state s in year t and α_1 is the main coefficient of interest. X_{idst} includes individual-level controls such as child age, child gender (takes a value 1 for female), and household-level controls such as mother's age, mother's years of education and household size.

We include district fixed effects (υ_d) to account for time-invariant district-level characteristics such as long-standing differences in governance, demographics, or crime reporting practices. We also include state-year fixed effects (γ_{st}) to absorb all shocks and policies that are common across districts within states in a given year. Standard errors (ϵ_{idst}) are clustered at the district level to account for within-district serial correlation in crime.

The identifying assumption is that, conditional on these controls and fixed effects, changes in district-level crime rates are uncorrelated with unobserved determinants of learning outcomes. In other words, any remaining variation in $CrimeRate_{dst}$ is assumed to be as-good-as-random with respect to children's test scores.

However, some challenges may limit the extent to which this assumption holds. First, unobserved time-varying district-level shocks – such as changes in education spending, infrastructure, or local governance – could be correlated with both crime and learning. To partially address this, we control for average night-time lights at the district level, a widely used proxy for economic activity (Asher, Lunt, Ryu Matsuura, & Novosad, 2021; Henderson, Storeygard, & Weil, 2011).

Second, state-level factors may evolve differently over time—for example, due to state-specific reforms, demographic transitions, or changes in bureaucratic capacity. To account for this, we include state-specific linear time trends, which allow for flexible, long-run changes in each state's trajectory. Similarly, while district fixed effects account for time-invariant differences across districts, districts with different characteristics could trend differently over time. To address this, we interact initial district-level characteristics from the 2011 Indian Census with linear time trends and show that our results remain robust.[5]

A third limitation stems from spatial aggregation in the data. The district is the lowest identifiable geographic unit in both the ASER and NCRB data and the level at which the data can be merged. This may obscure *within-district* heterogeneity in crime exposure. For example, a child living in a relatively safe neighbourhood of a high-crime district may experience far less risk than a peer in a hotspot, and vice versa. This introduces a form of measurement error in our key independent variable. If this measurement error is classical (i.e., uncorrelated with unobserved determinants of learning), our estimates would be biased towards zero. But if exposure is systematically related to unobserved household or school characteristics – such as selective sorting into safer areas – then the direction of bias is unclear. Relatedly, we also show that our results are robust to aggregating the entire analysis to the district level.

Further, characteristics that vary within districts – such as neighbourhood safety, local governance or community-level socioeconomic disadvantages – may influence both crime rates and learning outcomes.

[5] Specifications that include district-specific time trends absorb much of the identifying variation in crime, leading to coefficients that are both smaller in magnitude and statistically insignificant, likely due to overfitting.

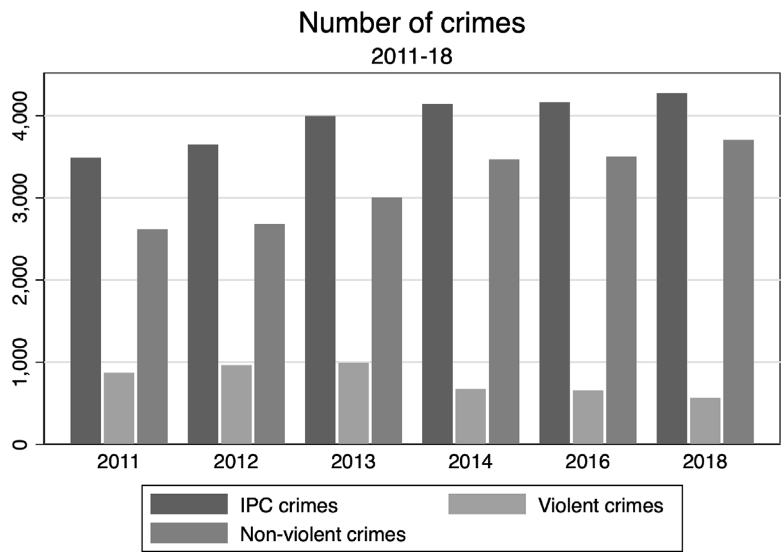

Fig. 1. Crimes in India, 2011–2018.
Source: Authors' calculations using data from National Crime Records Bureau (NCRB).

To the extent that neighbourhood-level differences are correlated with observable household or individual characteristics (e.g., more educated parents choosing to live in safer neighbourhoods), our inclusion of child- and household-level controls (such as mother's education) in Eq. (1) partially addresses this. In addition, our robustness checks using the two-period panel from the India Human Development Survey (IHDS), discussed in Section 4.3, incorporate household fixed effects, which account for all time-invariant household (and by extension, sub-district) characteristics. Nonetheless, we acknowledge that unobserved time-varying heterogeneity within districts remains a limitation of the data.

Considering these challenges, we interpret our estimates as well-estimated conditional associations rather than individual-level causal effects. In Section 4.3, we implement a battery of robustness checks to assess the credibility and stability of these associations across alternative specifications.

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 crime data. 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 Fig. 1, there is an increase in the number of IPC crimes rising gradually from 3489 crimes in 2011 to 4273 crimes in 2018. This is driven by the non-violent crimes steadily increasing from 2617 in 2011 to 3706 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. 48 percent of the children are female and the average age is 10 years. 3 percent of the children are not enrolled, consistent with enrolment rates being very high in India. The average age of the surveyed children's mothers is 34 years and they have 4 years of education. 45 percent of children have mothers with at least primary education completed. The average household size is over 6 and 45 percent of children come from households with above median number of assets (based on type of housing, availability of electricity, and ownership of mobile phone and television).[6]

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	2 495 078	

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.

4.2. Main results

Table 2 presents the main findings using Eq. (1), with right-hand side variables added sequentially. In columns 1 and 2, we regress math

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

Table 2
Association between crime and standardized test scores.

	No controls or FE		District & state-year FE		Controls & FE	
	Math score (1)	Reading score (2)	Math score (3)	Reading score (4)	Math score (5)	Reading score (6)
Violent crime per 1000	0.023	0.011	−0.062***	−0.043**	−0.057***	−0.039**
	(0.024)	(0.020)	(0.019)	(0.019)	(0.018)	(0.018)
R-squared	0.000	0.000	0.109	0.080	0.162	0.120
Observations	2 385 033	2 385 033	2 385 033	2 385 033	2 385 033	2 385 033
Controls	No	No	No	No	Yes	Yes
State-Year FE	No	No	Yes	Yes	Yes	Yes
District FE	No	No	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 violent crime rate.

	Math score			Reading score		
	Lag 1 (1)	Lags 1–3 (2)	Lags 1–5 (3)	Lag 1 (4)	Lags 1–3 (5)	Lags 1–5 (6)
Violent crime per 1000	−0.057***	−0.056***	−0.053***	−0.037**	−0.035**	−0.036**
	(0.018)	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)
R-squared	0.162	0.162	0.162	0.120	0.120	0.121
Observations	2,375,815	2,356,719	2,329,063	2,375,815	2,356,719	2,329,063
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
	Math score			Reading score		
	Lead 1 (1)	Leads 1–3 (2)	Leads 1–5 (3)	Lead 1 (4)	Leads 1–3 (5)	Leads 1–5 (6)
Violent crime per 1000	−0.057***	−0.057***	−0.049**	−0.042**	−0.041**	−0.023
	(0.018)	(0.018)	(0.020)	(0.018)	(0.018)	(0.020)
R-squared	0.162	0.162	0.166	0.120	0.120	0.122
Observations	2,379,885	2,375,467	2,004,962	2,379,885	2,375,467	2,004,962
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%.

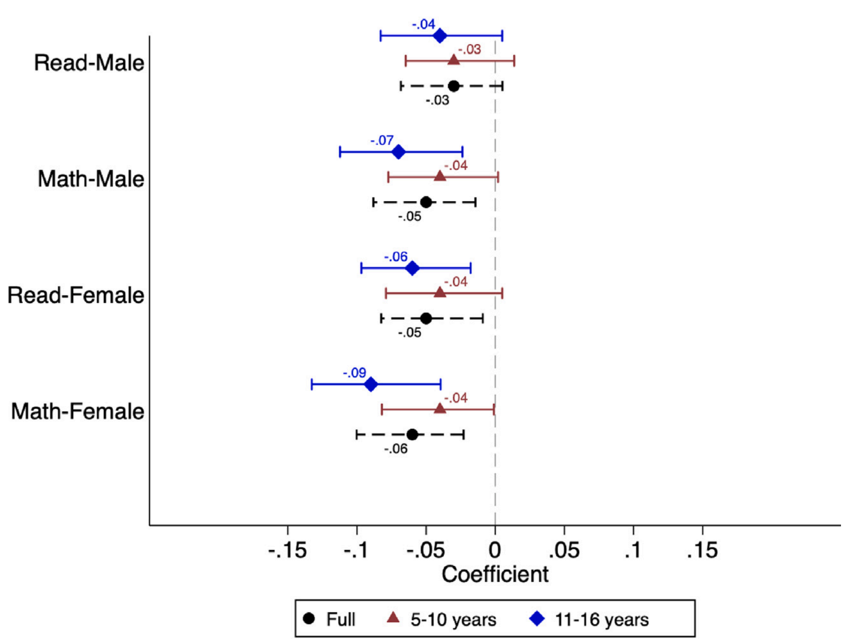

Fig. 2. Heterogeneity by age and gender. *Notes:* This figure shows point estimates and 95% confidence intervals.

and reading scores, respectively, only on the violent crime rate without any controls or fixed effects. In columns 3 and 4, we add district fixed effects and state-year fixed effects to account for unobserved spatial and temporal heterogeneity. Finally, in columns 5 and 6, we estimate the full specification as outlined in Eq. (1) by also including controls for child gender, child age, mother's age and education, and household size.

We find that violent crime is not significantly associated with learning outcomes in the most parsimonious specification in columns 1 and 2. However, the inclusion of district and state-year fixed effects in columns 3 and 4 yield significant negative associations, underscoring the importance of accounting for unobserved heterogeneity at these levels. Finally, upon adding the individual-level controls in columns 5 and 6, the coefficients are only marginally smaller as compared to those in columns 3 and 4 respectively, suggesting that our results are not sensitive to the inclusion of the controls. This helps to assuage concerns about potential bias from including non-exogenous covariates. In terms of magnitudes, coefficients from the full specification in columns 5 and 6 translate into a 1 SD increase in violent crime rate being associated with 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 magnitudes are at the 40th percentile of the distributions of standardized effect sizes on learning outcomes as noted in Evans and Yuan (2022).[7]

Further, these results are not driven by changes in children's enrolment or their school progression (Columns 1 and 2 in Table A1 in the Online Appendix).[8] 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 A1 in the Online Appendix).

Next, we examine the importance of non-violent crimes. Upon regressing test scores on non-violent crimes as well as total crimes (i.e., the sum of violent and non-violent crimes), it is evident that neither have economically or statistically significant associations with learning outcomes (Table A2 in the Online Appendix). Together with results in Table 2, this implies that it is the violent aspect of crime that is correlated with learning losses. This claim is further strengthened by estimating regressions where we control for both violent and non-violent crime rates simultaneously. Results in columns 5 and 6 of Table A2 in the Online Appendix show that only violent crime rates are associated with learning outcomes with coefficients on non-violent crimes being economically and statistically not significant.

We further disaggregate violent crime into three mutually exclusive categories based on the nature of harm involved: crimes against the person/body, property-related violent crimes, and public safety offences.[9] This allows us to examine whether certain types of violent crime are more strongly associated with learning outcomes. The results in Table A3 in the Online Appendix indicate that crimes against the person are more consistently associated with lower test scores, while property-related violent crimes and public safety offences also show negative associations although statistically insignificant. These patterns suggest that threats to physical safety may play a particularly important role in shaping the learning environment for children.

4.3. Robustness checks

In this section, we assess the robustness of our main findings to several potential concerns related to model specification, unobserved confounders, alternative specifications and sample exclusions.

A first concern is that time-varying factors may simultaneously influence both crime rates and children's learning outcomes. One such factor is district-level economic activity. As district-level GDP data are not available for India during our study period, we proxy for economic activity using annual district-level night-time lights intensity, which has been widely used as a measure of local economic activity in both global and Indian contexts (e.g., Asher et al., 2021; Henderson et al., 2011).[10] Results in columns 1 and 2 of Table A4 demonstrate that our findings reported in columns 5 and 6 of Table 2 are robust to the inclusion of this time-varying district-level variable.

Second, to allow for unobserved factors that may evolve differently across states over time, we include state-specific linear time trends. These trends capture state-specific gradual changes in education policy, institutional reforms, or other socioeconomic factors that could be correlated with both crime and educational outcomes. The estimated coefficients on violent crime remain stable and statistically significant with the inclusion of these state-specific trends, as shown in columns 3 and 4 of Table A4. Further, in columns 5 and 6 of Table A4, we also allow districts with varying characteristics to trend differently by interacting district-level characteristics (i.e., literacy rate, share of rural population, share belonging to disadvantaged caste groups, number of primary schools per capita, number of middle schools per capita and share of villages with paved roads) from Census 2011 with linear time trends.[11] Our main results are robust to this too.[12]

As a third robustness check, to address concerns with our main analysis relying on repeated cross-sectional data, we estimate the crime-learning relationship using the IHDS two-period household panel data, which conducts tests with children aged 8–11 in each household (as described in Section 2.3). While we cannot form a child-level panel due to the timing of the IHDS waves and the age restriction on test administration, the panel structure allows us to include household fixed effects, thereby controlling for all time-invariant household characteristics that could confound the relationship between crime and learning outcomes. We regress children's test scores (reading and math) on the district-level violent crime rate, including household fixed effects, survey wave fixed effects, and controls for child age and gender. Results in columns 1 and 2 of Table A5 show that math and reading scores are negatively associated with violent crime even after accounting for household-level factors. In columns 3 and 4, we include district fixed effects, consistent with our main specification, and find similar results. Overall, these findings suggest that our results are robust to using a different dataset, estimation strategy, and time period.

We next examine the robustness of our results by including lagged and lead values of the violent crime rate. Given the crime data availability, we can include up to five leads and lags. In the upper panel of Table 3, we sequentially add lagged violent crime rates in addition to contemporaneous crime as follows: first, year $(t-1)$ only; then, years $(t-1)$ through $(t-3)$; and finally, years $(t-1)$ through $(t-5)$. The lower

[7] 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.

[8] 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.

[9] Crimes against the body: murder, culpable homicide not amounting to murder, dowry deaths, attempt to commit murder, grievous hurt, kidnapping and abduction, and rape; property-related violent crimes: robbery, dacoity, and preparation and assembly for dacoity; and public safety offences: riots and arson.

[10] Gridded night lights data are obtained from the SHRUG open data platform (Asher et al., 2021), available annually from 1992–2021, sourced from DMSP and VIIRS, and calibrated for consistent time series estimation. It should be noted, however, that the performance of nightlights data for predicting GDP has been found to vary based on the data source used (Gibson, Olivia, Boe-Gibson, & Li, 2021).

[11] Census 2011 data accessed via the SHRUG open data platform (Asher et al., 2021).

[12] We also explore specifications that include district-specific linear time trends. However, since violent crime varies at the district-year level, including district-specific trends absorbs much of the identifying variation in the data, leading to small and statistically insignificant estimates.

panel presents results from including the corresponding lead values. For math scores, the coefficient on contemporaneous crime remains robust and statistically significant with the inclusion of lagged and lead crime variables. For reading scores, the coefficient remains robust when including lags but becomes smaller and loses statistical significance when 4- and 5-year leads are included. These results indicate that the main effects are driven mainly by contemporaneous crime exposure rather than past or anticipated future crime.

A fifth 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. For males and females, employment and marriage respectively are the primary reasons for migration.[13] 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 (2016), we can internalize this concern by aggregating the data to a larger unit and conducting the regressions at the district level. Results in Table A6 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.

Sixth, 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 A7 and A8 respectively in the Online Appendix. Table A7 shows that exposure to higher crime is associated with learning losses in that children are less likely to recognize double-digit numbers (column 2), carry out subtractions (column 3) and divisions (column 4) with no significant correlation with basic knowledge as assessed by single-digit number recognition (column 1). For reading ability, in Table A8, we find that exposure to higher crime is negatively associated wth learning at all levels, but the coefficient is not statistically significant for being able to read at least a paragraph (column 3).

Seventh, 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.

Finally, 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, when 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.

[13] In fact, Bell et al. (2015) estimate that India has the lowest rate of internal migration in a sample of 80 countries.

Table 4
Heterogeneity by socioeconomic status.

	Panel A: Heterogeneity by maternal education			
	Math score		Reading score	
	At least primary educated (1)	No primary education (2)	At least primary educated (3)	No primary education (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 (1)	≤median assets (2)	>median assets (3)	≤median assets (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%.

4.4. 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 the crime-learning associations vary based on child gender and age in Fig. 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 (2021) and Muralidharan and Prakash (2017)). These results show that the correlations are statistically significant for most age-gender sub-groups. The results appear to be more negative for the older age group and for girls, although none of these sub-group coefficients are significantly different from one another.

We next investigate whether there is heterogeneity based on the family's socioeconomic status (SES) in Table 4. We use two standard indicators of SES that are available in ASER[14]: (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. The direction of heterogeneity by socioeconomic status is theoretically ambiguous. On the one hand, wealthier and more educated households may be better positioned to mitigate the effects of crime-related disruptions on children's learning—through safer transport, private tuition, or school-switching strategies. On the other hand, they are also more likely to access and act upon information about local crime—via newspapers, television, mobile phones, or social networks—which could heighten their responsiveness and lead to stronger effects.

[14] Caste and religion – widely used proxies of socioeconomic status in India – are not elicited in ASER.

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%.

Therefore, the net relationship between socioeconomic status and the impact of crime on learning is ultimately an empirical question.

Previous studies have shown that the effects of shocks are smaller in cases where mothers are educated. For instance, Andrabi, Daniels, and Das (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. In terms of wealth, Beegle, Dehejia, and Gatti (2006) find that households with more assets are better able to offset agricultural shocks. Using data from India, Nordman, Sharma, and Sunder (2022) find that education spending and child work are less susceptible to the adverse effects of rainfall shocks in households where mothers are educated. They also show that the effects of rainfall shocks on educational spending are smaller for 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 negatively correlated with crime where the mother has no primary education (columns 2 and 4) as compared to where she has at least primary education (columns 1 and 3), and the difference is statistically significant for 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 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 and 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 at or below median crime rates in 2010, the year just preceding the start of the study period. Consistent with the two papers cited above, we find that the crime-learning link is more negative in districts that have below median crime rates (columns 2 and 4). Moreover, the baseline crime exposure gap is significant for reading scores (p-value = 0.098).[15]

Finally, we investigate whether violent crime has varying associations with learning at different points 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 violent crime-learning association is negative and quite similar throughout the distribution. For reading scores, violent crimes have more negative associations for those who perform poorly on the reading test (i.e., those in the 10th and 20th percentiles) but less so (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 examine a range of potential demand-side and supply-side explanations that could underlie the findings reported in the previous section. Demand-side mechanisms refer to behavioural responses by children, parents, and households, while supply-side mechanisms relate to the quality and availability of schooling inputs such as teachers. Because the ASER household survey does not include information on these mechanisms, we draw on other large-scale, representative surveys to explore them. While this exercise has limitations, it provides suggestive evidence on channels that may help explain the observed associations.

5.1. Child mobility

Crime can affect children's mobility, as reflected in their school attendance and participation in work. This may stem from increased parental risk aversion that limits children's mobility outside the home. Indeed, research shows that crime exposure can heighten risk aversion (e.g., Jakiela & Ozier, 2019; Brown et al., 2019).

Although our crime data are aggregated at the district level, they plausibly shape household perceptions. Mass media such as newspapers and television – used regularly by a majority of rural adults (IIPS and ICF, 2021) – along with informal channels like word-of-mouth or village discussions, likely amplify awareness of violent incidents. Thus, district-level crime may serve as a proxy for the broader informational and security environment that influences household decision-making around education.

As previously discussed, while there is no correlation between violent crime and school enrolment and progression rates (Table A1 in the Online Appendix), it may still reduce children's actual attendance. While individual-level school attendance data are unavailable, the ASER School Survey collects enrolment and attendance data at the grade level.[16] Regressing attendance rates (i.e., share of enrolled children present on the day of the survey team visit) on violent crime shows a negative and significant association in primary schools but not in upper primary schools (Table A10 in the Online Appendix).

[15] We also examine whether the crime-learning relationship differs by overall development and state capacity using the widely cited "BIMARU" versus non-BIMARU classification. BIMARU states (Bihar, Madhya Pradesh, Rajasthan, Uttar Pradesh, Jharkhand, Chhattisgarh, Uttarakhand) have historically lagged on social and economic indicators. As shown in Table A9 in the Online Appendix, the negative association between violent crime and learning is concentrated in BIMARU states, while in non-BIMARU states the coefficients are small and not statistically significant.

[16] 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 school information is recorded based either on the enumerators' observations (e.g., student attendance, teacher presence, availability of facilities) or school records (e.g., enrolment, number of teachers, etc.). We use this data for six rounds spanning 2011 to 2018.

Table 6
Estimated effect of violent crime on child work.

	Any work (1)	Farm work (2)	Non-farm work (3)	Animal care (4)	Wage work (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 for sample of children aged 5–16. 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%.

We also draw on data from the two waves of the IHDS, as described in Section 2.3, to examine children's participation in economic activity—a widely used proxy for mobility, especially in the context of exposure to violence (e.g., Borker, 2021; Siddique, 2022; Mishra, Mishra, & Parasnis, 2021). The IHDS records children's involvement in farm work, non-farm household enterprises, animal care, and wage work. We construct a binary indicator for "any work", equal to one if the child participated in any such activity. Estimating regressions with household and month–year fixed effects, in Table 6, we find that violent crime is negatively correlated with children's likelihood of engaging in any work as well as all individual categories, except wage work. Together, these findings suggest that reduced child mobility in response to violent crime could play a role in explaining our results on learning outcomes.

5.2. Household economic status

Exposure to crime can affect households' economic status by affecting their labour market outcomes, which in turn could influence how resources are allocated towards children's education through an income effect. For example, Velasquez (2020) finds that drug-related violent crime in Mexico adversely affects employment status and hours worked, especially for self-employed workers. In the Indian context, Siddique (2022) finds that female labour force participation reduces following media reports of violence against women. Chakraborty, Mukherjee, Rachapalli, and Saha (2018) also show that the perceived threat of sexual violence adversely affects women's engagement in work.

We use data from the IHDS panel. To investigate adult work outcomes, we construct measures of adults' engagement in farm work, non-farm household enterprises, animal care and wage work, as well as a binary measure for 'any work' that equals one if the adult is involved in any of these activities. From the household-level panel, we 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 columns 1–5 of Table 7, we see that higher violent crimes rates are associated with a lower probability of adults engaging in any work, farm work, and animal care. For household-level income and assets (columns 6 and 7), the coefficients are not statistically significant and appear imprecisely estimated. Overall, while there is some evidence of reduced likelihood of adult work, we do not find clear evidence of an income effect pathway that could explain our main results on test scores.

5.3. Mental health

There is now a rapidly growing literature showing that crime imposes psychological costs not just through direct victimization but also through local exposure (e.g., Alloush & Bloem, 2022; Cornaglia et al., 2014; Dustmann & Fasani, 2016). The intuition is that exposure to local area 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 & 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., Michaelsen & Salardi, 2020; Sharkey, Tirado-Strayer, Papachristos, & Raver, 2012). Parental stress and insecurity caused by community violence can also be transmitted to children, which could also explain the negative crime-learning relationship even among those not in school (Table A1 in the Online Appendix).

To that end, we examine whether exposure to crime is associated with worse mental health in India. We use the two waves of the SAGE data described in Section 2.4. As individuals from over 7600 households were interviewed in both 2003 and 2007, we use household- and survey-year fixed effects in our estimation framework. The outcomes are measures of depression and worry/anxiety. Results in Table 8 show that being a victim of crime is correlated with a higher likelihood of depression and anxiety (columns 1–2) as well as higher reported levels of these variables (columns 3–4). This pattern is consistent with findings from other studies described above and suggests that mental health may be one pathway linking exposure to violent crime and children's educational outcomes.

5.4. School inputs

In this section, we discuss possible school-related supply-side responses to crime that may 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 & Rocha, 2017).[17]

To examine the relationship between crime and 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, the reported average working hours per day of teachers are available separately for grades 1–4 and grades 5–8. We use these measures as outcomes in Table 9. As we have a school-level panel, the regression analysis includes school fixed effects and year fixed effects with standard errors clustered at the pincode (or postcode) level. Column 1 shows that exposure to violent crime is associated with a lower stock of teachers, and more so for female teachers as compared to male teachers (columns 2 and 3). Further, columns 4 and 5 show that an increase in the violent crime rate is associated with higher number of working hours per day for teachers

[17] 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 A11 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 the availability of physical infrastructure.

Table 7
Estimated effect of violent crime on household economic status.

	Any work (1)	Farm work (2)	Non-farm work (3)	Animal care (4)	Wage work (5)	Log (Household Income) (6)	Asset index (7)
P.C. violent crime	−0.010**	−0.017**	−0.002	−0.030*	−0.004	−0.037	0.024
	(0.004)	(0.008)	(0.003)	(0.016)	(0.007)	(0.038)	(0.030)
Mean of dep. var.	0.702	0.317	0.092	0.287	0.403	10.324	10.557
R-squared	0.249	0.049	0.057	0.040	0.218	0.028	0.075
Observations	172,543	172,591	172,591	172,516	172,539	55,774	56,371
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey Month–Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The outcome variables are from the India Human Development Surveys of 2004–05 and 2011–12. Regressions in columns 1–5 are at the individual-level for adults aged 18–60 while columns 6–7 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 (1)	Worried (2)	Depression (cont.) (3)	Worry (cont.) (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%.

in both primary and upper primary grades. This pattern suggests that with fewer teachers, those remaining on staff may be working longer hours. As student enrolment appears stable, this also implies higher student–teacher ratios, which have been shown to be associated with poorer learning outcomes.[18]

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, lower adult labour force participation, worse mental health, and lower availability of teachers in schools. However, because we draw on different datasets to examine each mechanism, we are unable to assess the relative importance of these channels.

6. Conclusion

This paper examines the relationship between local area crime and human capital accumulation, focusing on learning outcomes of children in India. We combine multiple years of district-level crime data from the National Crime Records Bureau with information from the 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 individual and household controls. Our empirical strategy uses the district-year variation in crime to estimate the crime-learning gradient.

We find that increases in violent crime are associated with lower learning outcomes with non-violent crimes showing no such association. These results are robust to a range of checks, including controlling for district-level time-varying factors that are potentially correlated with both crime and learning outcomes. We also find that the relationship between crime and learning is heterogeneous based on the socioeconomic status of 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 examine the potential channels by using a variety of representative datasets from India. We find support for the following mechanisms that can explain the negative associations between violent crime and children's learning outcomes: on the demand-side, we find evidence of poorer mental health, reduced child mobility, and lower engagement of adults in work, and on the supply-side, we find lower availability of (female) teachers because of violent crime.

While most existing literature, with a few exceptions, has focused on episodic violence, this study using nationally representative data, highlights the potential effects of day-to-day crime on human capital accumulation, an often-overlooked cost of such crime. Additionally, the fact that people regularly experience crime in their daily lives affects equitable growth and development by widening socioeconomic disparities in learning. While our estimates are for India, we believe these findings may extend to other low- and middle-income countries where such crime is endemic.

CRediT authorship contribution statement

Smriti Sharma: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Naveen Sunder:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.worlddev.2025.107161.

Data availability

The data used in the analysis is largely publicly available. If selected for publication, the authors will submit a replication code to replicate all results in the paper.

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

Table 9
Violent crime and teacher availability.

	Total teachers (1)	Female teachers (2)	Male teachers (3)	Working hours/day (grades 1–4) (4)	Working hours/day (grades 5–8) (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%.

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